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Part 1 - Summary Details

Please use your TAB key to complete Parts 1 & 2.

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Executive Summary

Provide a one page Summary of your research that is not commercial in confidence, and that can be published on the World Wide Web. Explain the main outcomes of the research and provide contact details for more information. It is important that the Executive Summary highlights concisely the key outputs from the project and, when they are adopted, what this will mean to the cotton industry.

This project has demonstrated the implementation of adaptive control systems at commercial cotton cropping sites. The control simulation framework VARIwise has been used for the simulation and development of irrigation control strategies. The framework potentially provides site-specific irrigation volumes and timing to be determined in autonomous irrigation, either for uniform or variable-rate irrigation application.

Field evaluations of the control strategies were conducted on siphon and centre pivot irrigation systems in Jondaryan, QLD utilising a weather, soil and plant sensors, control strategies and irrigation control hardware. The siphon and centre pivot irrigation trials produced yield improvements of 11% and 7% respectively, and water use reductions of 12% and 4% respectively. Higher water reductions were achieved in surface irrigation systems than overhead irrigation systems because of the larger volumes of irrigation water applied. Adoption of these irrigation control systems would provide improved and automated irrigation management and labour savings to the industry.

An on-the-go plant sensing system was developed to estimate plant density, plant height (for leaf area index calculation), flower count (for square count calculation) and boll count, as required to calibrate the industry crop production model OZCOT for the control strategy operation. This sensing system was standalone and platforms were developed that enabled mounting to on-farm vehicles (e.g. moped) and irrigation machines. The centre pivot irrigation trial indicated that plant data input was preferable to soil data input for model-based irrigation control strategies.

There is limited control hardware currently commercially available for surface irrigation, and commercial variable-rate solenoid-based irrigation adjustment hardware is available for centre pivots and lateral moves. For the purposes of the field evaluations in this project, an irrigation control hardware system was developed that was independent of the irrigation system. This was based on adjusting the flow rate using a remotely controllable ball valve

and servomechanism and could be installed in-line with siphons and droppers on irrigation machines.

Over 90% of the Australian irrigated cotton industry uses surface irrigation. Further enhancements to the system would entail investigating the spatial resolution of irrigation application adjustment for both surface and overhead irrigation systems. This would potentially determine the data requirements of surface irrigation control systems, reduce the sensors requirement (leading to reduced cost of the system) and increase the practicality and uptake of the final system. In addition, the control strategies could be extended to consider fertiliser application in surface irrigation systems, as the efficiency of the fertiliser application is expected to be related to the efficiency of the irrigation application.

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1. Background

1.1 SITE-SPECIFIC IRRIGATION CONTROL STRATEGIES

Site-specific irrigation enables the delivery of irrigation water where and when it is required in the field. Commercially available hardware is available that can adjust the application from centre pivots and lateral moves; however, wide adoption of these systems is limited because of a lack of decision-support to determine irrigation application.

The irrigation control framework VARIwise was created to developed, simulate and compare site-specific irrigation control strategies (McCarthy et al. 2010). This involves: (i) dividing the field into smaller, controllable sub-areas named ‘cells’; (ii) assigning soil and plant parameters to each cell; (iii) calibrating the corresponding crop model for each cell; and (iv) executing a crop production model within in each cell. VARIwise has been used to determine the optimal data input types and resolution for each control strategy in simulation (McCarthy et al. 2011; McCarthy et al. 2012).

Two general types of adaptive control strategies have been implemented in VARIwise that can be applied to irrigation: sensor- and model-based. Sensor-based control strategies use the difference between a measured and target variable to update the irrigation application, whilst model-based control strategies determine irrigation application that best achieves the desired future crop performance as predicted by a calibrated crop production model. Two implemented sensor-based strategies are:

- **Iterative Learning Control** (ILC) which uses the error between the desired and measured soil-water deficit after the previous irrigation to adjust the irrigation volume of the next irrigation event; and
- **Iterative Hill Climbing Control** (IHCC) which involves: (i) dividing the field into zones according to a pre-measured variability map; (ii) selecting ‘test cells’ in each zone to evaluate different irrigation volumes; (iii) applying test irrigation volumes to each test cell; (iv) evaluate the crop response to the previous irrigation before the next irrigation is applied; and (v) calculating a performance index for each test cell in each zone to evaluate the response of the soil and/or plant to the irrigation volume.

A model-based strategy utilised in VARIwise is:

- **Model Predictive Control** (MPC) which involves using a calibrated cotton model to simulate and evaluate various site-specific irrigation volumes and timings, and then implements the irrigation scheme (at that moment) that will maximise the cotton yield at the end of the crop season. The model calibration procedure (as required by MPC) must be emulated as there is no field data to calibrate the model in the simulation environment. This is achieved by utilising two crop models, each with different crop and soil properties where the output of one crop model (with the 'actual' field conditions) calibrates a second crop model (i.e. the 'base' model). The calibrated base model is used to optimise the irrigation management, whilst the actual model is used to determine the performance of the model predictive control strategy after the irrigation management options for the crop season have been determined.

Generic adaptive control systems have three major components: (i) sensor data feedback; (ii) control strategy that uses data feedback to determine system input; and (iii) actuator hardware to adjust system inputs. The transfer of data between these components where VARIwise incorporates the control strategy is shown in Figure 1.1.

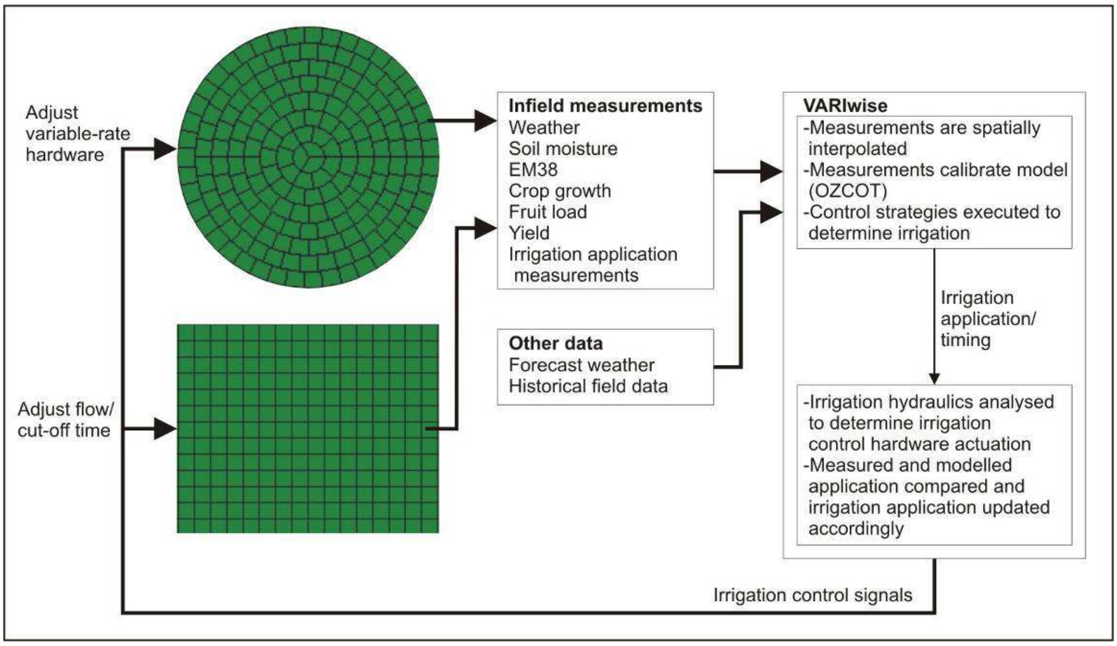

Figure 1.1: Generic adaptive control system applied to surface and overhead irrigation systems

These components of an adaptive control system could be implemented in a non-autonomous irrigation system where sensing is achieved through manual field observations and irrigation application hardware is manually adjusted. For example, siphons could be manually stopped or irrigation machine speed manually changed.

1.2 PROJECT AIM AND OBJECTIVES

The control strategies in VARIwise were previously only evaluated in simulation on centre pivots and lateral moves. However, this approach can be applied to any irrigation system.

Hence, this project aimed to integrate VARIwise with existing automation and control systems for surface and overhead irrigation, demonstrate and validate the integrated system in the field, and further develop the software. The objectives and milestones of this project follow:

1. Adapt VARIwise to optimise seasonal management of surface irrigation

1.1 Incorporation of surface irrigation capability in VARIwise

1.2 Evaluation of alternative control strategies and relevant scales of data input

1.3 Integration of VARIwise with automation hardware and software

1.4 Field evaluation and exploration of potential for combined system

2. Investigate integration with commercial systems for variable-rate applications from centre pivots and lateral moves

2.1 Assessment of feasibility

2.2 Integration of VARIwise with variable-rate hardware and testing

2.3 Field implementation on centre pivot or lateral move and evaluation

3. Incorporate a self-learning capability into VARIwise

3.1 Review of self-learning models and feasibility in agriculture

3.2 Review of data requirements for adaptive control

3.3 Validation of crop model against field data

4. Incorporate hydraulic and sprinkler simulation models for centre pivots and lateral moves

4.1 Incorporation of hydraulic model

4.2 Validation of model (in conjunction with milestone 2.3)

4.3 Investigation of sprinkler models for incorporation in VARIwise

1.3 REPORT OUTLINE

This report is structured around the three components of irrigation control systems that were investigated to achieve the project milestones, as follows.

- Weather and soil sensors are available off-the-shelf; however, measuring plant response over a field often requires manual visual assessment of the crop which is not practical in site-specific and automated control systems; hence, a plant sensing system was developed and is described in **Section 2**.
- **Section 3** presents a review of crop production models used in irrigation control strategies and an evaluation self-learning models and the OZCOT model calibration (milestones 3.1, 3.2 and 3.3).

- The extension of VARIwise control strategies to surface irrigation required utilisation of hydraulic models and a comparison between modelled and measured irrigation data as described in **Section 4** (milestones 1.1, 4.1 and 4.2).
- Wind drift and evaporation can influence the irrigation from sprinkler systems and simulations were conduct to evaluate the effect of these parameters on adaptive irrigation control performance in **Section 5** (milestone 4.3).
- **Section 6** describes commercially available irrigation adjustment hardware and the design for the system implemented in the field trials (milestones 1.3, 2.1 and 2.2).
- Control strategies were compared and evaluated in the field on a surface irrigation system as described in **Section 7** (milestones 1.2 and 1.4).
- **Section 8** presents the fieldwork conducted to evaluate sensor- and model-based control strategies on a centre pivot irrigation machine (milestone 2.3).
- **Section 9** gives conclusions, recommendations for further research and extension opportunities, and outputs during the course of the project.

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2. Development of a sensing system for automated cotton plant measurement

2.1 INTRODUCTION

Physiological plant responses can indicate levels of crop water stress and are useful for informing on-farm management decisions. Plants can indicate water availability and stress, since plants automatically integrate the atmospheric and soil factors that affect plant water status (Kramer and Boyer 1995). For example, minimal stress (i.e. too much irrigation or rain) on a cotton plant can be visually identified from excessive vegetative growth, increased leaf area, extended flowering cycle timeframe, boll capacity and poor boll retention (Gibb et al. 2004). Plant density also directly influences soil-water extraction, light interception, humidity and wind movement, which in turn influence plant height, branch development, fruit location and size, crop maturity and yield (Hake et al. 1991).

Plant measurements would be beneficial for feedback in automated irrigation control systems (McCarthy et al. 2013). Automated irrigation control systems can be model-based which involve determining irrigation application and/or timing by: (i) calibrating a crop production model using the required input soil/plant parameters; and (ii) repeatedly executing the calibrated crop model with different irrigation volumes and timing to determine which irrigation produces the desired performance objective (maximum yield, water use efficiency).

For the Australian cotton production model OZCOT (Wells and Hearn 1992), plant parameters that are required to calibrate the model are plant density, leaf area index, square (flower bud) count and boll (fruit) count. However, measurement of these parameters requires labour-intensive visual assessment of individual plants. This process could effectively be automated using cameras to automatically acquire images of the crop, and image analysis algorithms to analyse the image and extract fruit load and vegetation information.

Existing sensing systems that automatically measure plant parameters have used light sensors to measure leaf area index (Tewolde et al. 2005) and plant height (Searcy and Beck 2000); image analysis of camera images to determine internode length (McCarthy et al. 2010a), nitrogen status (Noh et al., 2005) and plant size (Shrestha and Steward, 2005); and multispectral properties using narrowband imaging (Carter and Miller 1994). A review of machine vision based sensors is presented in McCarthy et al. (2010b).

This paper presents the development of a plant sensing system to estimate plant density, leaf area index, square count and boll count. Three platforms for carrying the sensing system over a broad-acre field were also developed. The particular platform utilised in the field situation depends on the type of on-farm machinery available and the size of the field site. This paper describes:

- the selection of the sensing hardware for data collection (Section 2.2);
- the development of the image analysis algorithms (Section 2.2);
- the development of the platforms to carry the sensing system over broad-acre cropping (Section 2.3); and
- a field evaluation of the sensing system and platforms on cotton crops (Section 2.4).

2.2 SENSING SYSTEM DATA CAPTURE AND PROCESSING

Camera-based identification of plants, flowers and bolls in a cotton crop may involve using visual characteristics of the crop, e.g. the fact that bolls are elliptical in shape. Spectral response of the crop may also aid the image processing to enable easier extraction of plant features. The spectral response of different cotton plant materials is shown in Figure 2.1.

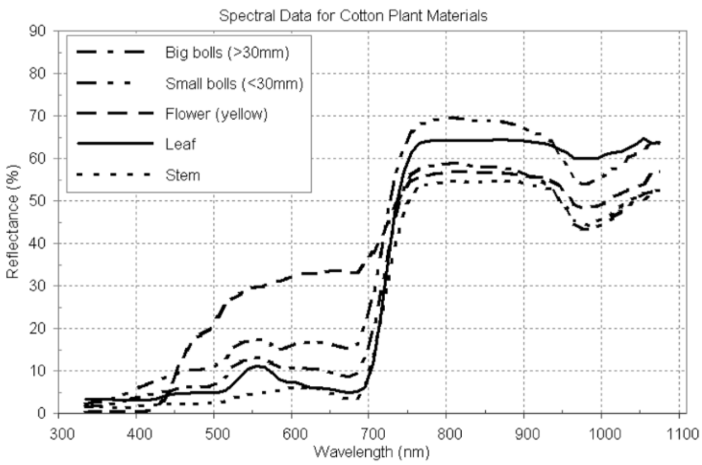
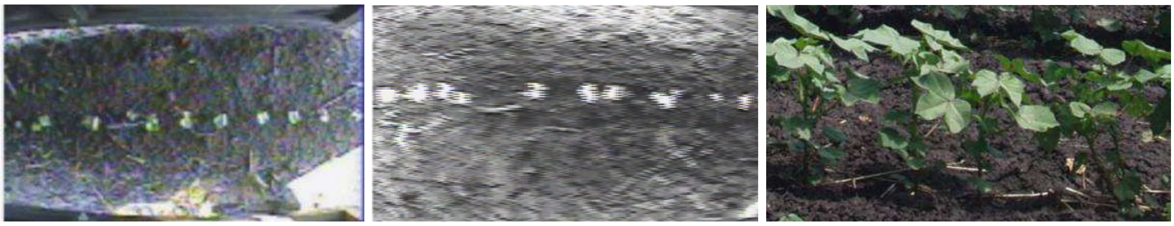


Figure 2.1: Spectral response (325-1075 nm) of cotton plant materials (McCarthy 2009)

2.2.1 Plant density estimation

In cotton, plant density typically ranges between 8 and 12 plants/metre (CSD 2009). Early in the cotton season, the plant density could be estimated using a camera that captures a top view of the crop and an image analysis algorithm that counts the number of green objects in the image (e.g. Figure 2.2(a)). As the cotton plants develop, their branches intertwine and only a side view of the crop can be used to count the plants by detecting the main stem of each cotton plant (Figure 2.2(b)). However, plant density may be required for optimising irrigation events from the start of the season, and the determining the plant density earlier in the season enables earlier irrigation optimisation. Hence, a top view of the crop obtained following full germination was used to determine plant density.



(a) (b) (c)

Figure 2.2: (a) Top view of 4 week old cotton seedlings; (b) top view 850 nm image of 4 week old cotton seedlings; and (c) side view of ten week old cotton plants

As illustrated in Figure 2.1, leaves have the highest reflection at wavelengths 750-940 nm. Hence, an infrared filter was used to increase the contrast between the leaves and the soil and stubble. The following image analysis algorithm was developed and implemented on infrared images:

Identify potential plants:
1. Identify leaf (white) pixels from image.
2. Assign each identified leaf pixel to a potential plant number index if connected to another leaf pixel.

Size analysis:
1. Count number of pixels in each potential plant identified.
2. If $50 < count < 800$ then a plant is detected and accumulate plant count.

2.2.2 Square count estimation

Squares (flower buds) appear similar to leaves and are difficult to visually distinguish in a two-dimensional image of a cotton crop (Figure 2.3(a)). Because squares are leaf-like material their spectral response is similar to leaves. However, flowers could be distinguished from leaf material in the red wavelengths 450-700 nm (Figures 2.1 and 2.3(b)) and used to estimate the number of cotton squares (with a time delay). There are typically 21 days from first formation of a pinhead square to white bloom (Quinn and Kelly 2011), and flowers typically last for seven days, being white on the day of opening, pink on the second day, red on the third, day and drying and falling from the plant within the following four days exposing the developing boll. Hence, the measured flower counts could be used to back-calculate the square counts using equation 2.1:

$$B_{n=t-7}^{t-21} = F(t) + B_n \qquad (2.1)$$

where:

B = square count on day n

n = days after sowing

t = day of flower count measurement

F = flower count on day n

The following flower identification and counting algorithm was implemented on red images of the crop:

Identify potential flowers:
1. Identify flower (white) pixels from image.
2. Assign each identified flower pixel to a potential flower number index if connected to another flower pixel.

Size analysis:
1. Count number of pixels in each potential flower identified.
2. If 50 < count < 400 then a flower is detected and accumulate flower count.

(a) (b)

Figure 2.3: (a) Visible image of square (circled); and (b) 670 nm image of flowers on cotton plant where white areas indicate presence of flower

2.2.3 Boll count estimation

Small bolls have the highest reflectance of all cotton materials at wavelengths 450-950 nm, whilst large bolls have reflectance similar to leaves and stems at 450-950 nm (Figure 2.1). However, the shape of the bolls can be distinguished from leaves as the cotton bolls are elliptical in shape whereas leaves are irregular in shape (Figure 2.4). The bolls are arranged on a cotton plant in a range of orientations; hence, to identify bolls from their shape, the width and height of each identified object was compared using following algorithm on the infrared images of the crop:

Identify potential bolls:
1. Identify boll (lighter) pixels from image.
2. Assign each identified boll pixel to a potential boll number index if connected to another boll pixel.

Shape analysis:
1. Count width (W) and height (H) of each potential boll identified.
2. If H < W < 1.2 * H or W < H < 1.2 * W then still potential boll.

Size analysis:
1. Count number of pixels in each potential boll identified.
2. If 50 < count < 800 then a boll is detected and accumulate boll plant count.

(a) (b)

Figure 2.4: (a) Visible image of boll; and (b) 850 nm image of bolls on cotton plant where bright elliptical areas indicate presence of boll

2.2.4 Leaf area estimation

Measurement of leaf area index (LAI) typically requires destructive sampling. However, since adequate experimental relationships between LAI and plant height have been developed for cotton (e.g. ASCE 1996; Richards et al. 2002; Kerby et al. 2009), the plant height was measured and used to estimate LAI. A relationship has been developed for Australian surface irrigated cotton (Richards et al. 2002) as follows:

$$LAI = 0.00347 \times Height - 0.0352 \qquad R^2 = 0.914 \qquad (2.2)$$

This relationship was developed using two cotton varieties with normal (broadleaf) and okra (lobed) leaf shapes and grown under industry standard cultural conditions. The relationship between cotton height and LAI is expected to vary with different irrigation management strategies and cotton varieties. In addition, the cotton varieties are continuously updated and the varieties used to develop this relationship are not currently widely grown. However, the experimental relationship considers some varietal differences as two leaf shapes were used and the relationship would be adequately applicable to current cotton varieties.

The desired plant height measurement is the distance from the cotton's cotyledons (the lowest leaves on the plant) to the plant terminal (tuft of unfurling leaves at the top of the main stem) (Hake et al. 1996). Plant height can be measured using non-contact distance sensors that emit either infrared, ultrasonic or laser signals and detect reflection time to estimate distance to the closest object (i.e. the plant).

An ultrasonic distance sensor was used to estimate plant height because, in general, infrared distance sensors do not work reliably in direct sunlight (due to interference between the sensor's infrared emissions and the infrared components of sunlight), and lasers are commonly available only for longer range measurement (typically 5-300 metres). These sensors would be mounted above the crop canopy and the height estimated by subtracting the measured distance between the sensor and the crop and the distance between the sensor and the ground. The distance to the ground would be determined from measurements to the ground without any crop.

2.2.5 Measurement system assembly

In the developed platforms, an ultrasonic distance sensor was used to estimate leaf area index, and top view camera images were used to estimate plant density and fruit load. Red wavelengths can be used to identify flowers in the image and infrared wavelengths can be used to identify leaves and small bolls. To achieve this, a red filter (670 nm) and infrared filter (850 nm) were positioned in front of a camera in the crop. Images of the crop in the visible waveband were also captured for comparison with the red and infrared images: this required an infrared cut filter (1000-1500 nm) to remove the infrared light.

2.3 SENSING SYSTEM PLATFORMS

Three platforms were developed for conveying the sensing system over broad-acre crops (Figure 2.5). Each sensing system platform also used a miniature PC (Fit-PC2, Compulab) that recorded images from the connected cameras, and data from an ultrasonic distance sensor and GPS module (66 channel LS20031, LOCOSYS Technology Inc.). The platforms were:

(i) **On-ground platform** that involved a four-wheeled, shaded trolley containing the sensors. This system was manually pushed over the field and is only practical for small scale data collection.

(ii) **On-farm vehicle mounted platform** that consisted of a steel frame and one tyre attached to the side of an on-farm vehicle (here a moped) which was driven over the field. This platform enabled more extensive data collection and it is envisaged that this system would be mounted to a tractor to collect data in a commercial field situation.

(iii) **Irrigation machine mounted platform** was attached to a centre pivot irrigation machine to collect data as the irrigation machine passed over the field. A self-contained, waterproof and solar-powered sensing unit was developed and suspended from the supporting structure of an irrigation machine. This platform then did not require any on-ground travel for data collection, but of course provided data only for a single circle in the irrigated area. (However, multiple sensors along the irrigation machine or a motor-driven scanning system alone each span would increase the sensor spatial resolution.)

The same ultrasonic distance sensor was used for all three platforms. An ultrasonic distance sensor was selected with a sensing range of 3 - 400 cm as the maximum distance between the platforms and the ground was 275 cm (Table 2.1). This sensor has accuracy of 3-4 cm and a beam width of 55° (model SRF05, Devantech).

(a) (b) (c)

Figure 2.5: Platforms for cotton fruit load and vegetation estimation that traverse the field via: (a) on-ground self-contained unit; (b) on-farm vehicle mount; and (c) irrigation machine mount

Table 2.1: Specifications of sensors used in each platform configuration

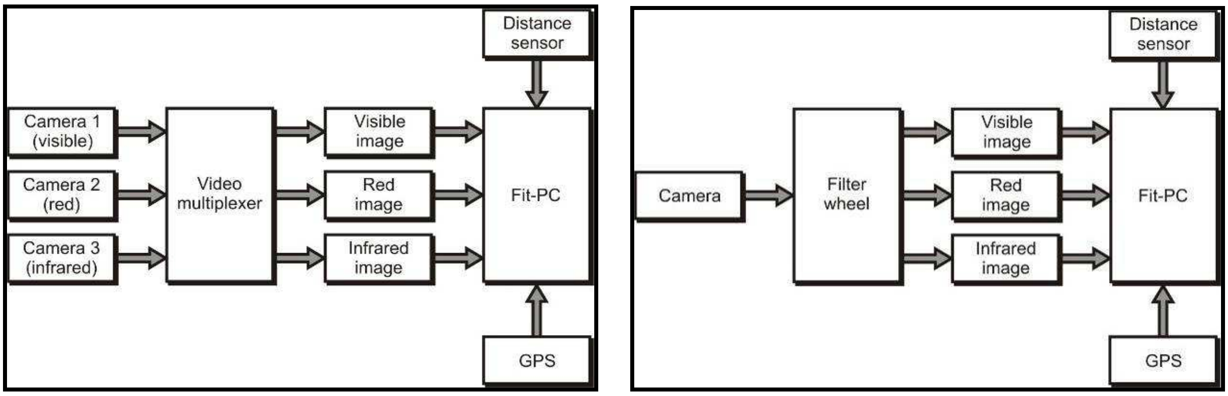
Platform	Travel speed (km/h)	Ground data capture interval (cm)	Sensor distance from ground (cm)	Sensor	Field of view	
					Width (cm)	Height (cm)
On-ground	3.60	50	110	Distance	107	115
				Camera	143	107
Vehicle mounted	12.00	170	100	Distance	104	104
				Camera	130	97
Irrigation machine mounted	0.18	20	235-275[1]	Distance	245-286	245-286
				Camera	305-356	228-267

[1] This distance depends on position of sensor along the span of the irrigation machine, as the supports that the sensors are mounted to are closest to the ground at the centre of the span and furthest from the ground at the towers.

2.3.1 Ground-based sensing platforms

During data capture, the ground-based platforms (i) and (ii) travelled significantly faster than the irrigation machine mounted platform (iii) (Table 2.1); however, the sensing system was required to capture the red, infrared and visible waveband images of the crop simultaneously. This was achieved using three cameras (Figure 2.6(a)) feeding images into a video multiplexer (4-channel Colour Video Quad Processor, Jaycar). This multiplexer transferred the three images in parallel to a computer, together with a corresponding distance sensor measurement and GPS location.

The on-ground sensing systems consisted of three board cameras using infrared-sensitive image sensors (1/3 inch CCD Sony Effio DSP). Each camera captured a 640 x 480 pixel image and had a 4 mm wide angle lens to increase the field of view to 78º. The on-ground sensing platforms also contained ten 20 W halogen lamps to provide uniform controlled lighting.



(a) (b)

Figure 2.6: Data collection hardware for: (a) on-ground and vehicle-mounted platforms; and (b) irrigation machine mounted platform

2.3.2 Irrigation machine mounted platform

Irrigation machines typically travel at approximately 3 m/min (0.18 km/h, Table 2.1) and each span is stationary for the majority of any irrigation event. Hence, the camera images could effectively be simultaneously captured at the three wavelengths using one camera and a filter wheel containing three filters (670 nm, 850 nm and infrared cut (Figure 2.6(b)). For each waveband, the PC captured an image and sent a control signal to filter wheel to rotate ready for the next image to be captured. A USB webcam with the infrared cut filter removed was used (Logitech C920). This camera also had a field of view of 78º and the focal length was fixed to 40 cm.

2.4. VALIDATION OF SENSING SYSTEM FOR COTTON

2.4.1 Methodology

The three sensing system platforms were evaluated on cotton variety Sicot 74BRF during three cotton seasons in Jondaryan, Queensland to compare the sensor estimations and manual measurements of plant height, plant density, flower count and boll count. The ground-based sensing system was evaluated on a furrow irrigated cotton field in the 2010/11 and 2011/12 seasons; and the on-farm vehicle and machine mounted sensing system were evaluated on a centre pivot irrigated cotton field in the 2012/13 season.

The on-ground platform was manually pushed down the cotton rows and manual measurements were taken in eight locations in the field on each date of data collection. The vehicle-mounted platform was attached to a moped and driven over the field at approximately

12 km/h and manual measurements were taken. Four irrigation machine-mounted platforms were developed and mounted on a centre pivot irrigation machine. Measurements were manually collected during the vehicle-based platform evaluation at seven locations in the field on each measurement date.

The measurements were taken between October and February spanning each cotton season. Plant density measurements were collected four weeks after sowing in each season of the trial. For each sample, ten plant density and height measurements were manually collected and averaged. For the flower and boll counts, manual measurements for ten plants were taken and averaged over the distance covered by the ten plants. The sensor estimations of the plant parameters were averaged across the field of view specific to each camera and sensing platform (Table 2.1).

2.4.2 Results and discussion

Sensor estimations for the three sensor platforms and manual measurements of plant density, flower count, boll count and plant height are compared in Figure 2.7. Table 2.2 presents a comparison of the performance across the three sensor platforms.

Plant density

The plant density was generally overestimated; however there was a high goodness of fit (Figure 2.7(a)). The overestimations were caused by falsely identifying weeds or stubble in the image as small cotton plants. The plant density sensor accuracy was relatively uniform across the three sensor platforms (Table 2.2). This is because plants were easily distinguishable from soil in the background in the infrared waveband.

Flower count

The sensing system generally underestimated the flower count but a high goodness of fit was achieved (Figure 2.7(b)). This is because the cotton plant flowers later in the cotton season when the plant and leaf area index are large, lead to the occlusion of a proportion of the flowers by the cotton leaves. However, only fully occluded flowers would not have been detected, as partially occluded flowers still have a high reflectance in the red waveband.

The on-ground sensing platform produced a higher goodness of fit than the vehicle- and irrigation machine-mounted sensing platforms (Table 2.2). This is because the on-ground platform provided the crop with controlled lighting under a shroud where there was even and soft lighting. Using the sensing platforms without a shroud and under bright sunlight, some leaves reflected the light and caused bright spots in the image which were incorrectly identified as flowers.

Boll count

Across the three sensing platforms, the boll count was underestimated by an average of 37% (Figure 2.7(c)). This is because later in the cotton season, the bolls lower on the plant were more difficult to detect and became fully occluded in a top view of the crop as the crop canopy closed.

Partially occluded bolls would also not have been detected as the boll identification used shape analysis to detect elliptical bolls. Only small bolls had a distinguishable response to light compared with the leaves and stems (as shown in the spectral response of different cotton plant materials in Figure 2.1). Hence, larger bolls would only have been detected if not occluded by leaves.

Full sunlight under the vehicle- and irrigation machine-mounted sensing platforms caused some inaccuracies in the identification of small bolls as the bright leaves would reflect the light (Table 2.2). However, for large bolls, the shape analysis reduced false positives caused by the sunlight.

Plant height

The plant height estimated using the ultrasonic distance sensor was highly correlated to the measured plant height (Figure 2.7(d)). The sensor had a stated accuracy of ±4 cm, whilst in a cotton crop the sensor had an accuracy of approximately ±6 cm. This inaccuracy was caused by the sensor taking measurements at regular intervals along the crop rows, which would consist of readings both in gaps between cotton plants (which would underestimate the plant height), and from the highest leaves of the plant above the crop's main stem (which would overestimate the plant height).

The three sensing platforms detected height uniformly across the three sensing platforms (Table 2.2). This is because the ultrasonic distance sensor uses sonar to detect the first echo which is the closest object (Hamilan et al. 2008) and this signal is not affected by sunlight.

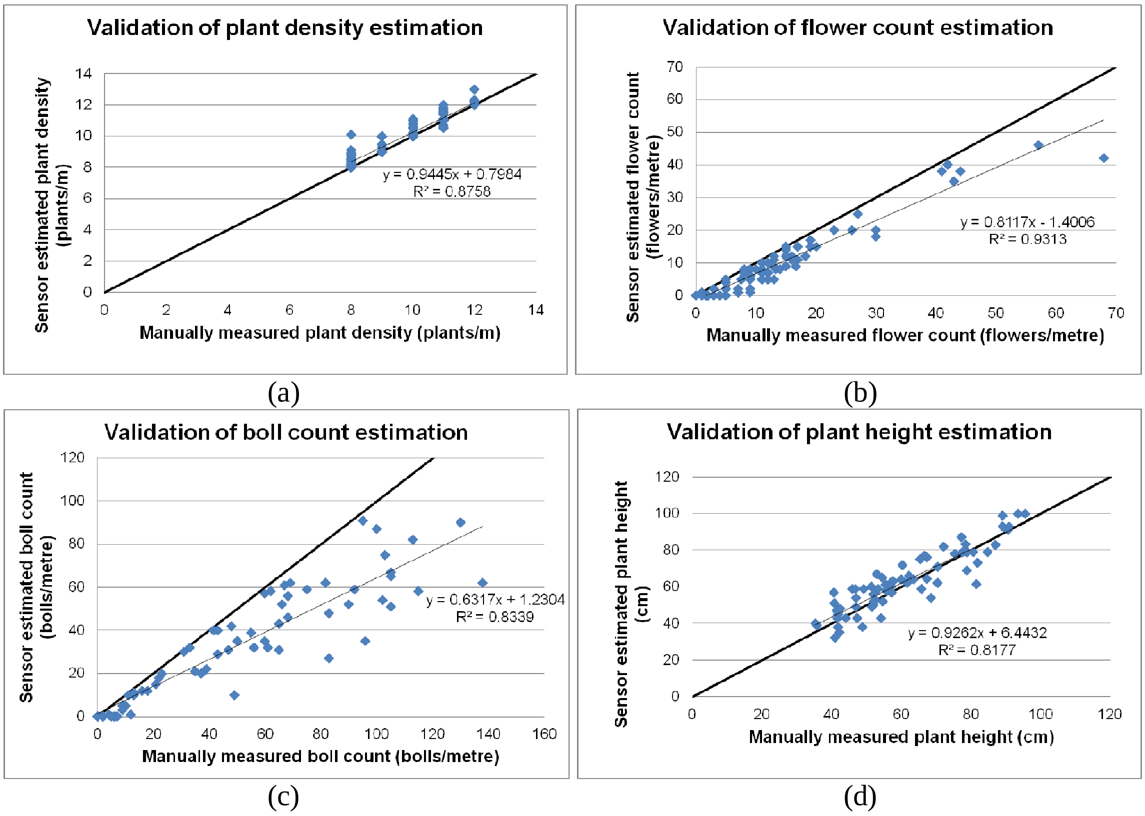


Figure 2.7: Comparison of sensor estimations and manual measurements of: (a) plant density; (b) flower count; (c) boll count; and (d) plant height for the three sensor platforms with 1:1 lines

2.5 CONCLUSIONS

A cotton plant sensing system was developed and evaluated on cotton crops over three seasons using three mounting platforms. Ultrasonic distance sensors were capable of providing accurate, repeatable distance measurements of the plant both under sunlight and when mounted from an irrigation machine 275 cm from the ground. Plant density could be accurately determined using infrared images of cotton seedlings. Colour and shape-based analysis on top-view cotton images provided an estimation of the flower count and boll count. As the season progressed, cotton bolls were less accurately extracted using a top view of the crop due to occlusion from leaves and the reduced reflectance in the infrared waveband. This cotton plant sensing system provides a high resolution of spatial data capture that may be required by site-specific irrigation control systems.

Table 2.2: Performance of the vegetation and fruit load estimation using the three sensor platforms where *y* is the manual measurement and *x* is the sensing platform estimation

Measurement	Platform	Regression	Goodness of fit
Plant density	On-ground	$y = 0.9291x + 0.9694$	0.8775
	Vehicle mounted	$y = 0.8982x + 1.2317$	0.8412
	Irrigation machine mounted	$y = 1.0021x + 0.2639$	0.8878
Flower count	On-ground	$y = 0.8789x - 1.8163$	0.9755
	Vehicle mounted	$y = 0.9282x - 3.1364$	0.9421
	Irrigation machine mounted	$y = 0.7047x - 0.2157$	0.9083
Boll count	On-ground	$y = 0.6848x - 0.8946$	0.8686
	Vehicle mounted	$y = 0.5911x + 2.8166$	0.8101
	Irrigation machine mounted	$y = 0.6332x + 1.5766$	0.8248
Plant height	On-ground	$y = 0.8956x + 9.8592$	0.8512
	Vehicle mounted	$y = 0.8123x + 11.465$	0.8224
	Irrigation machine mounted	$y = 1.1142x - 5.2177$	0.8301

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3. Utilisation of crop production models in adaptive control strategies

3.1 INTRODUCTION

Accurate process models are required to predict the performance of crops under different irrigation management options using model-based control strategies. The control strategies then assess the simulated output to determine the treatment that best achieved the desired performance objectives. The performance may be assessed on either long-term objectives (yield or water productivity) or short-term objectives (e.g. soil-water, fruit load).

Data transfer between VARIwise and the external crop models are specifically programmed in VARIwise (for cotton, the model OZCOT is utilised). An update to the crop model may require additional programming due to changes in input and output data formatting. VARIwise also currently has the capability to calibrate the OZCOT model using measured input data. However, this procedure is computationally intensive as it involves adjusting the plant and soil parameters in input files, executing the model and reading the model output files iteratively until the model output reflects the measured field data on the measurement days.

For a universal self-learning crop model (e.g. a neural network-based) the model would automatically adjust the parameters using the available measured data. A self-learning model would enable the control strategies to be easily transportable between crops and crop seasons to accumulate site-specific databases and models of measured data. A universal self-learning crop model in VARIwise would not require maintenance with each updated to the model.

This section evaluates the performance of the OZCOT model calibration using field data collected in a 2011/12 surface irrigation trial (Section 3.2). The potential to implement self-learning crop models in adaptive irrigation control is then discussed (Section 3.3).

3.2 CALIBRATION OF CROP PRODUCTION MODEL OZCOT

3.2.1 Methodology

Seven furrows were monitored during a surface irrigation field trial in the 2011/12 cotton season in Jondaryan, QLD. This involved collection of soil-water measurements at three depths (30, 60 and 90 cm) and seven points in the field, and soil electromagnetic induction (EM) measurements and leaf area index, square count and boll count estimations at 1 m^2 resolution. The soil-water was estimated across the field by spatial interpolation based on the EM map.

The OZCOT model was calibrated within VARIwise at 320 points along each furrow (i.e. one measurement per metre). However, this spatial resolution of data input and the full range of data types may not be required to achieve model calibration of sufficient accuracy. An exploration of data input combinations and spatial resolution was conducted in simulation to determine the data input requirements for adaptive control of surface irrigation.

This simulation study compared the irrigation application and yield using different combinations and spatial resolutions of data input for model calibration. Each simulation was assigned an identification number for reference (Table 3.1). Weather input was used in all scenarios as daily weather is required by the OZCOT crop model. The same spatial and temporal resolutions were used for both soil and plant datasets as EM and plant sensor measurements were collected on the same days.

Table 3.1: Data input combinations evaluated in simulation to determine irrigation application, where W denotes weather data input, S denotes soil data input, P denotes plant data input, and * denotes the actual irrigation measured in the field

ID #	Data input for control	Number of readings along furrow
1	W	0
2	WP	1
3	WP	3
4	WP	10
5	WP	320
6	WS	1
7	WSP	1
8	WS	3
9	WSP	3
10	WS	10
11	WSP	10
12	WS	320
13	WSP	320
14	WSP*	320

The measured data were then compared with the model calibrated using the full dataset input to validate the OZCOT crop model. Measurements of soil-water, leaf area index, square count, boll count and yield collected in 2011/12 were compared with the corresponding modelled data before and after model calibration on the days of EM surveys (for soil-water measurement) and plant sensor data capture.

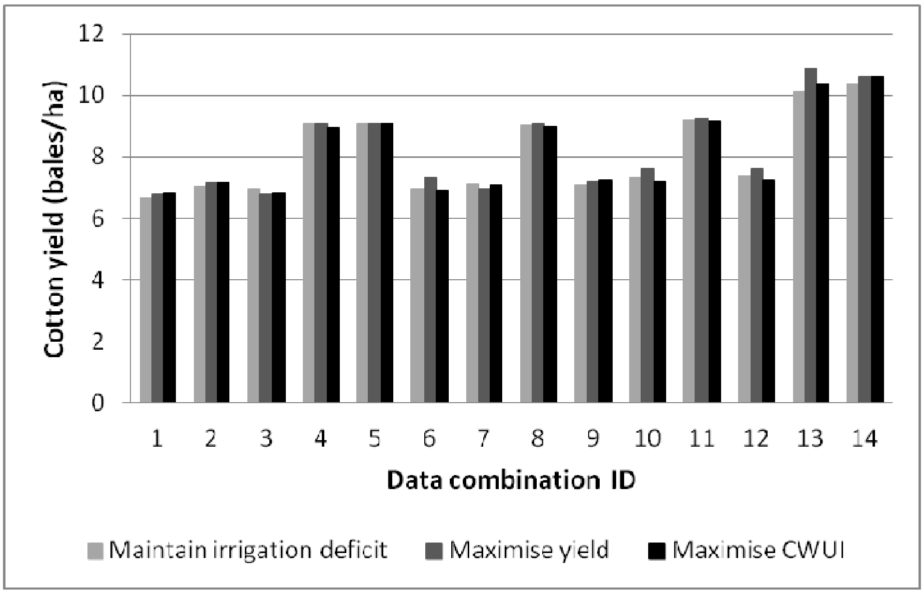
3.2.2 Results and discussion

The results of the simulations to evaluate data input requirements for model calibration are presented in Figure 3.1. Inspection of these results indicates the following:

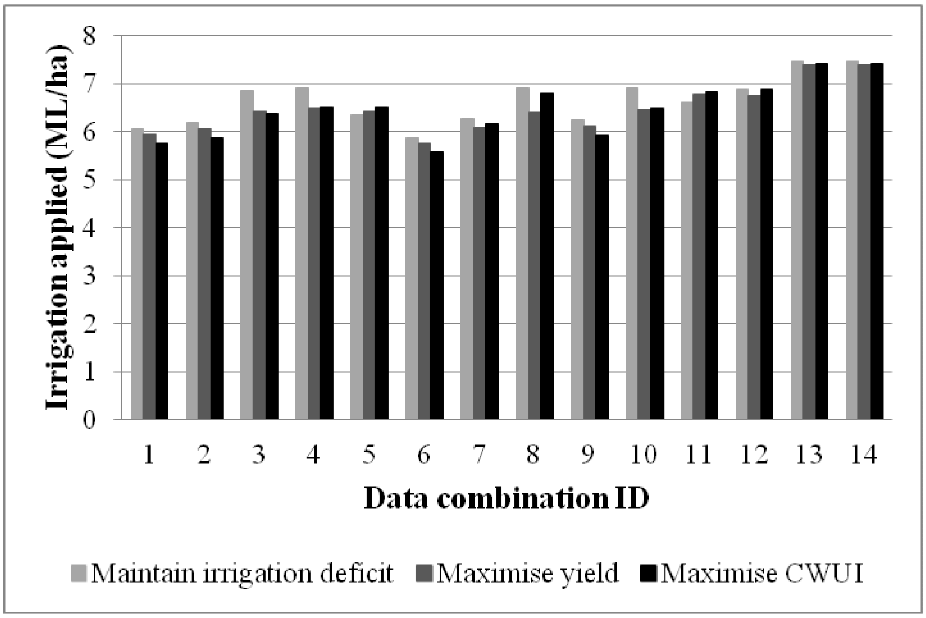
- The OZCOT model could be accurately calibrated with a 5% difference in simulated yield using all the field data (#13) compared with the field measurements (#14).
- The yield and irrigation application closest to the measured event was achieved using weather-soil-and-plant input measured at 10 points along each furrow (#11).
- Weather-and-plant data input produced yield and irrigation application closer to the field measurements than weather-and-soil data input.
- The yield was higher with a lower spatial resolution of soil and plant data than with a high spatial resolution of soil-and-weather data. This indicates that plant data (even at lower spatial resolution) is preferable to a high resolution of soil data without plant data.
- The MPC strategy that filled the soil profile generally applied more irrigation water than the other performance objectives. Maximising yield generally produced the same or higher yield than the other performance objectives.

Table 3.2 displays the comparison between field measurements and outputs of the model before and after calibration using all available weather, soil and plant data. The differences between the measured and modelled responses were averaged across the seven monitored furrows.

The largest variation between measured and pre-calibration modelled data occurred with soil-water with a 52% difference. There was variation in measured and pre-calibration modelled plant parameters of between 23 and 38%. Hence, OZCOT could more accurately determine plant parameters than soil-water. However, calibration of the model using only plant data input had a higher impact on yield than using only soil-water (from the comparison of data input combinations). This may be caused by the calibration of plant growth in OZCOT effectively also accounting for soil-water differences. Following calibration, the model accuracy significantly improved to between 5 and 15% of the measured data.



(a)



(b)

Figure 3.1: Simulated outputs of control strategies using different spatial data resolutions for calibration: (a) yield; and (b) irrigation application

Table 3.2: Average percentage difference between measured and modelled soil and plant parameters before and after model calibration

Measurement type	Average difference before calibration	Average difference after calibration
Soil-water	51.46 ± 11.53 % (102.24 ± 22.92 mm)	5.04 ± 4.17 % (10.01 ± 8.28 mm)
Leaf area index	22.84 ± 19.35 % (0.18 ± 0.15)	6.51 ± 2.53 % (0.05 ± 0.02)
Square count	31.71 ± 7.38 % (22.62 ± 5.26 squares/m²)	14.31 ± 4.85 % (10.21 ± 3.46 squares/m²)
Boll count	37.21 ± 26.88 % (32.45 ± 23.44 bolls/m²)	13.37 ± 7.66 % (11.66 ± 6.68 bolls/m²)
Yield	33.80 ± 6.06 % (3.56 ± 0.64 bales/ha)	4.53 ± 1.56 % (0.48 ± 0.17 bales/ha)

3.3 INVESTIGATION OF SELF-LEARNING CROP MODELS

Self-learning models involve using regression analysis to directly derive equations from infield measurements of the weather, soil and/or plant. This is in contrast to 'dynamic models' (e.g. OZCOT) that are developed from known dynamics of the soil-plant-atmosphere system (Wallach 2006). Hence, dynamic models may be extrapolated to other sites with different climatic and soil inputs because they are derived from known dynamics rather than from regression analysis of collected data (e.g. Protopapas and Georgakakos 1990).

Self-learning models have been developed and evaluated to relate yield, soil-water, soil texture, nitrogen use and supply and topography (Li et al. (2002) for cotton; Timm et al. (2003) for sugarcane; Wendroth et al. (2003) for barley). However, the developed models do not consider plant growth or climate during the crop season.

Crop production models utilised by VARIwise are used to evaluate multiple irrigation volumes and timings. To ensure the accuracy of a self-learning model for these evaluations, an extensive data set for a range of irrigation volumes and timings would likely be required. Self-learning models that are trained using insufficient data sets may be limited to much simpler representations of the soil-plant-atmosphere system than is possible with dynamic crop models. Hence, self-learning models would require extensive data collection which may not be practical for each new crop or field implementation of VARIwise. Self-learning models developed exclusively from field data are not feasible for irrigation management.

The accuracy of self-learning models may be improved by incorporating some known relationships into the model. However, this process does not present any advantages over calibrating the crop and soil parameters of an existing dynamic model.

An advantage of self-learning models is that their structure and the format of their input and output data are often independent of the crop type. Hence, there would be no specific programming requirements to incorporate different crop models in VARIwise. An alternative approach to overcome the data formatting differences between models is to incorporate a model framework (e.g. APSIM) in VARIwise which has standardised the structure of dynamic crop models. Hence, VARIwise has been extended to incorporate APSIM, which contains the models of a range of crops in Australia that can be used in feedback for control strategy simulations.

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4. Real-time, site-specific control of surface irrigation

4.1 SITE-SPECIFIC CONTROL OF SURFACE IRRIGATION

The centre pivot and lateral move irrigation implementations in VARIwise assumed that the optimal irrigation volume determined for each cell by the control strategies would be applied as desired. However, in surface irrigation systems, a specific irrigation volume cannot be directly applied to each cell in the field. This is because irrigation is applied to all the cells in each furrow from the head ditch and the irrigation application distribution in each cell is a function of the soil-water deficit, inflow rate/s (if temporally variable), cut-off time and infiltration characteristics. The optimal irrigation characteristics could then be determined by comparing the optimal irrigation distribution with a range of furrow irrigation distributions.

Classical equations that describe surface irrigation hydraulics are ‘Saint Venant equations’ and are available in the public domain and irrigation texts (e.g. Walker and Skogerboe 1987). These equations were used to: (i) determine irrigation infiltration to characterise the furrow irrigation which requires flow rate and advance measurements; and (ii) determine the closest irrigation distribution to the optimal distribution achievable with surface irrigation by comparing the simulated infiltrated depth along furrows for different flow rates and cut-off times.

In VARIwise, the field is managed using cells and the size and shape of these cells depend on the size and shape of the field. For centre pivot-irrigated fields the cells are sectioned, donut shaped sections, whereas for lateral move-irrigated fields the cells are rectangular. As fields of surface irrigation systems are typically rectangular in shape, VARIwise was updated to use rectangular shaped cells for surface irrigation systems. The cell width was taken to be the furrow spacing.

4.2 DATA TRANSFER BETWEEN HYDRAULIC MODEL AND VARIwise

4.2.1 Calculation of infiltration parameters

The movement of irrigation down a furrow with a particular inflow rate and cut-off time, and subsequent irrigation distribution, depend on the soil properties which can be characterised using infiltration parameters. The infiltration parameters for each furrow in the trial are required before the irrigation events can be controlled. This involves monitoring the flow rate and cut-off time along the required furrows for the first irrigation of the measured crop’s season and entering these measurements into a surface irrigation hydraulic model to determine the parameters. Current user interfaces for surface irrigation models that provide infiltration parameters are: WinSRFR (Bautista et al. 2009), SIRMOD (Walker 1997) and SISCO (Gillies et al. 2010). The user interface of SISCO was used to determine the infiltration parameters, and the output infiltration parameters were then manually entered into the user interface of VARIwise.

4.2.2 Simulation of irrigation events

The capability to determine control signals for site-specific surface irrigation was integrated into VARIwise. This involved using the VARIwise control framework to determine the required irrigation distribution along each furrow, and iteratively executing the hydraulic model at different cut-off times and inflow rates to determine the combination that produces the infiltration distribution closest to the optimal distribution. For each furrow and irrigation event, VARIwise executes a surface irrigation simulation procedure (the Saint Venant equations) using the measured the infiltration parameters, and different combinations of cut-off times and inflow rates. The hydraulic model outputs the infiltration depths for user-specific interval along the furrow as an array and transfers the output infiltration distribution into VARIwise. For each furrow (i.e. row of cells in VARIwise), this procedure is repeated at different flow rates and cut-off times to determine which combination produces the application closest to the optimal application.

4.3 DETERMINING IRRIGATION FLOW RATE AND/OR CUT-OFF TIME

The inflow rate and cut-off time was determined by comparing the irrigation distribution curve generated by the hydraulic model for a range of inflow rates and cut-off times, with optimal curve determined by VARIwise. This was achieved by calculating a performance index (*PI*) for each flow rate *Q* and cut-off time *t* as follows:

$$PI_{Q,t} = \frac{\sum_{d=0}^{N} \frac{S_{d,Q,t} - V_{d,Q,t}}{V_{d,Q,t}}}{N} \qquad (4.1)$$

where:

Q = flow rate (L/s)

t = cut-off time (minutes after start of irrigation)

d = distance along furrow

$S_{d,Q,t}$ = irrigation depth determined by hydraulic model for point d, flow rate Q and cut-off time t

$V_{d,Q,t}$ = irrigation depth determined by control strategy for point *d*, flow rate *Q* and cut-off time *t*

N = number of cells along the furrow

The *PI* is calculated for a range of inflow rates that are realistic in the field (from 0.5 to 2.5 L/S in steps of 0.1 L/s) and cut-off time (500 to 720 minutes in steps of 10 minutes) (Carter and Grabham 2004). The combination with the smallest *PI* was selected to be the irrigation characteristics to be implemented.

4.4 REAL-TIME IRRIGATION ADJUSTMENT

The advance curve and flow rate that corresponded closest to each optimal distribution was determined using the hydraulic model and VARIwise. During each irrigation event the flow rate and cut-off time in each furrow could be determined to reflect the performance of the current irrigation treatment using irrigation control hardware. This may be achieved by calculating the new optimal advance and infiltration curves using either one of the following approaches:

- Calculate new infiltration parameters using the advance and flow rate during the current irrigation event
- Calculate a scaling factor from the real-time advance rate and infiltration parameters from the previous irrigation event
- Adjust flow rate according to the difference between the target and measured advance trajectory

The flow rate adjustment options 2 and 3 compare the current irrigation performance to a prediction based on a full irrigation evaluation. However option 1 calculates the infiltration parameters based only on the current (incomplete) irrigation event. Hence, options 2 and 3 may be more accurate than option 1 because they incorporate the infiltration along the whole furrow rather only on part of the furrow.

For option 2, the scaling factor scales the infiltration curve (i.e. irrigation advance time versus distance along furrow) from an irrigation evaluation (Khatri and Smith 2006). Use of the scaling factor during the early stages of the irrigation was found to cause a significant loss of accuracy in irrigation characteristics (Langat et al. 2008). This approach has been evaluated in the field to determine the cut-off time (Koech et al. 2011). This required multiple advance rates along the furrow, and only one advance rate measurement during subsequent irrigation events. The Irrimate™ surface irrigation evaluation systems was used to measure furrow inflow and advance rate.

The adjustment of the flow rate according to the difference between the measured and target advance trajectory (option 3) is an alternate method. This has been evaluated in previous trials to achieve the desired advance and corresponding infiltration distribution (e.g. Katapodes and Tang 1990). This enables the implemented irrigation to be updated during the event if the predicted event differs from the actual event. These differences are potentially caused by infiltration parameters changing temporally through the season and potentially spatially along the furrow. Option 3 provides opportunity for enhanced spatial control of irrigation application distribution and hence was used to control the inflow rate in the presented fieldwork. This involved changing the flow rate during the irrigation event according to the difference between measured advance and advance corresponding to the optimal irrigation distribution.

4.5 EVALUATION OF SURFACE IRRIGATION HYDRAULIC MODEL

4.5.1 Methodology

Irrigation measurements were collected to evaluate the accuracy of the surface irrigation hydraulic model for use in VARIwise control strategies. This required monitoring of advance rate and inflow rate throughout an irrigation event. Seven siphons were instrumented with Octave ultrasonic flow meters (Arad Group, Israel) sensors and the output pulses every 10 L of flow were recorded with an onsite laptop. The cut-off time and advance times at four equally spaced locations along each furrow were manually measured for each furrow. The measured inflow rates, cut-off times and advance distances and times were manually entered into the SISCO user interface to: (i) determine infiltration parameters; (ii) simulate the irrigation event using the calibrated parameters; and (iii) compare the simulated and measured advance rates.

4.5.2 Infield conditions

One irrigation event was monitored during a pre-watering in Jondaryan, Queensland on 3 October 2011. The parameters required by the surface irrigation hydraulic model were measured before the irrigation event (Table 4.1) where the slope of the furrow was measured using a dumpy level (Figure 4.1).

Table 4.1: Input parameters for surface irrigation model

Input data type	Value	Units
Field length	320	metres
Roughness coefficient (Manning, *n*)	0.04	Nil
Row spacing	2	metres
Slope	0.0016011	metres/metre
Recycling efficiency	90	%
Furrow top width	0.8	metres
Furrow middle width	0.5	metres
Furrow bottom width	0.3	metres
Furrow maximum height	0.2	metres
Cut-off time	550	minutes

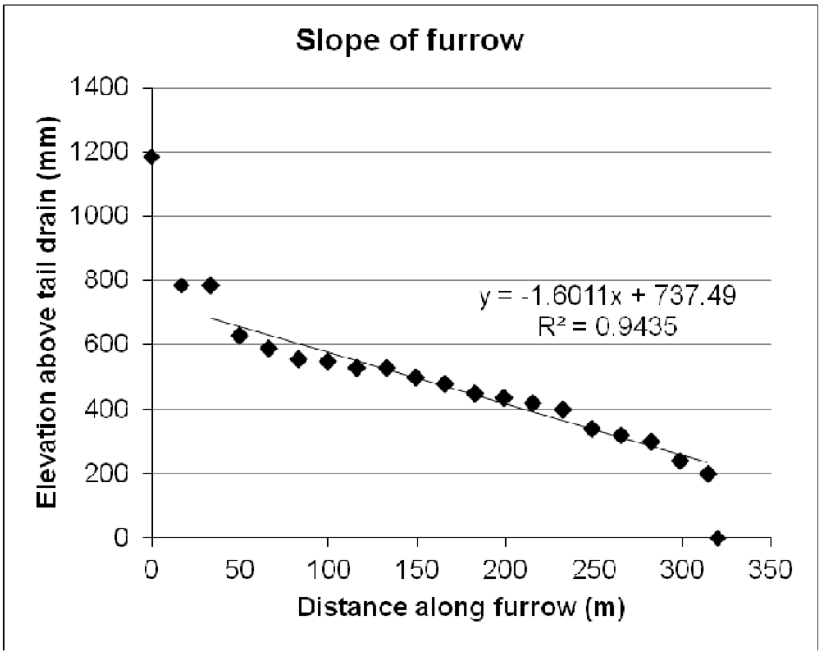
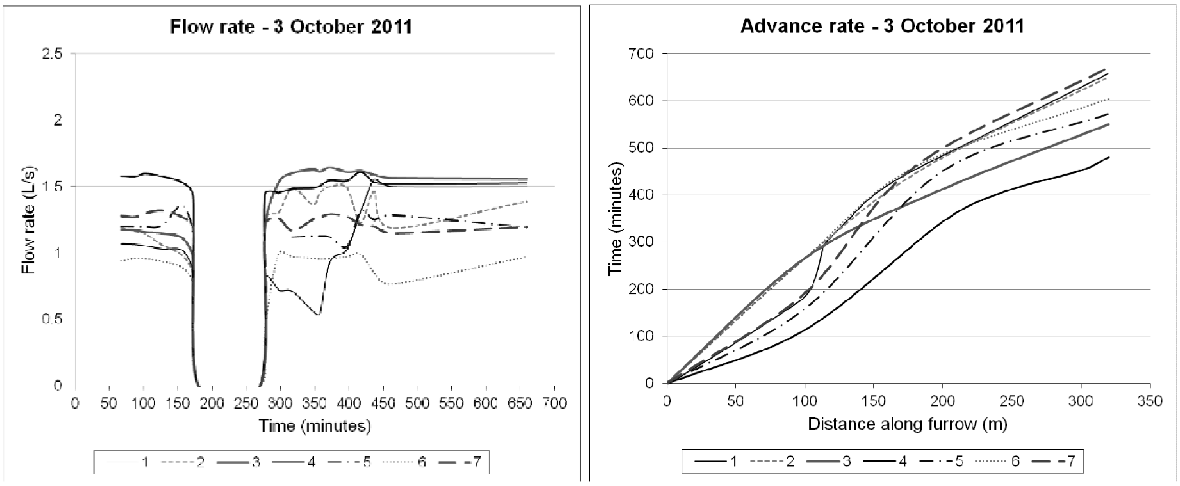


Figure 4.1: Slope of furrow in trial site

4.5.3 Results and discussion

The recorded flow rate and advance times are displayed in Figure 4.2 and 4.3, respectively. The siphons were stopped for 90 minutes after a pump blockage 180 minutes after the start of the irrigation (Figure 4.2). There is some variability in the flow rates between furrows which was caused by the meters floating in the irrigation bay and reducing the head. The flow rate was increased by partially burying the meters in the irrigation bays towards the end of the irrigation event. The flow rates through the siphons in the trial were approximately 30% less than those through siphons without the flow meters and valves (external to the trial). This is likely caused by debris in the water partially blocking filters in the flow meters. The filters in the flow meters were removed for subsequent irrigation events.

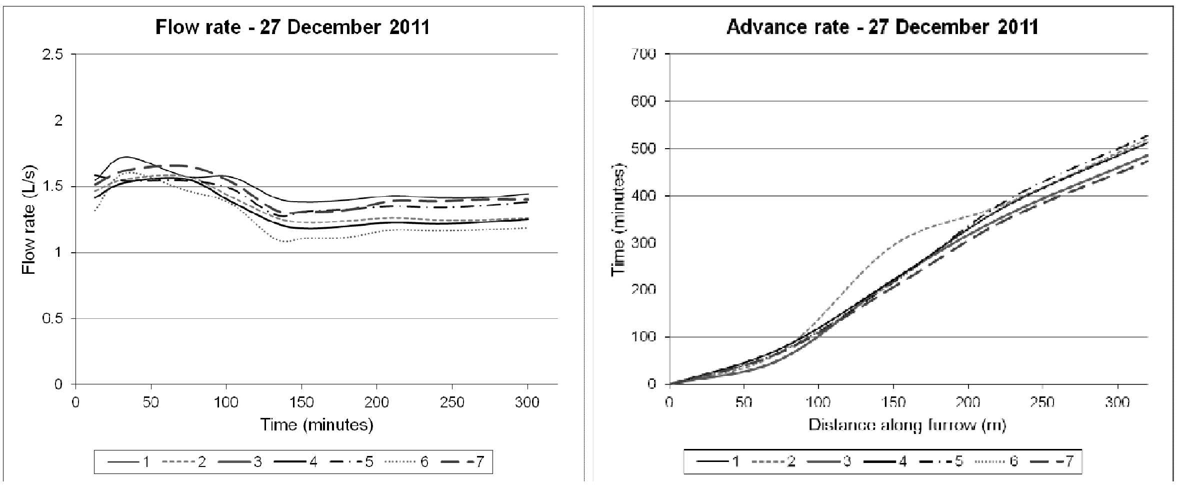


(a) (b)

Figure 4.2: Irrigation measurements from seven monitored furrows on 3 October 2011: (a) flow rate; and (b) advance rate

The flow and advance rates were entered in a hydraulic model to determine the infiltration parameters (Table 4.2). However, the infiltration parameters that were found using the measured data resulted in an average estimation error of 95%. Hence, a second irrigation event was monitored on 27 December 2011 to evaluate the model and determine the infiltration parameters (Figure 4.3) where the time for the advance front to reach four points along the furrows (75 m, 150 m, 225 m and 320 m) were measured.

Flow meter 3 was found to be faulty during the irrigation event on 27 December 2011 and was only working intermittently; hence, the flow rate in furrow 3 was assumed to be same as furrow 4 for this irrigation event. The flow rates during the second irrigation event were more consistent than the irrigation event on 3 October 2011 and there were no disruptions to the irrigation application. The flow rate reduced after the first 100 minutes as the water level in the head ditch settled. The advance rates followed a similar trend for each furrow.



(a) (b)

Figure 4.3: Irrigation measurements from seven monitored furrows on 27 December 2011: (a) flow rate; and (b) advance rate

The infiltration parameters were determined for the irrigation event on 27 December 2011 (Table 4.2). The surface irrigation model was then parameterised with the calibrated infiltration parameters and run to simulate the irrigation advance. Figure 4.4 shows high correlation between the measured and simulated curves. This indicates that a surface irrigation model can be used with calibrated infiltration parameters under infield conditions to estimate the irrigation characteristics.

Table 4.2: Infiltration parameters determined by surface irrigation model for irrigation event on 27 December 2011 with C=0

Furrow	a	k (m^3/min/m)	f_0 (m^3/min/m)
1	0.0589565683777	0.0794507416362	0.0000656496551
2	0.1030337398	0.0725864583	0.0
3	0.0799598857140	0.0705296081201	0.0000088132909
4	0.0912000045368	0.0725864583404	0.0
5	0.0935643628830	0.0752141703366	0.0000184720707
6	0.1177393446349	0.0592889365379	0.0
7	0.0706102845648	0.0774184895738	0.0000288359741

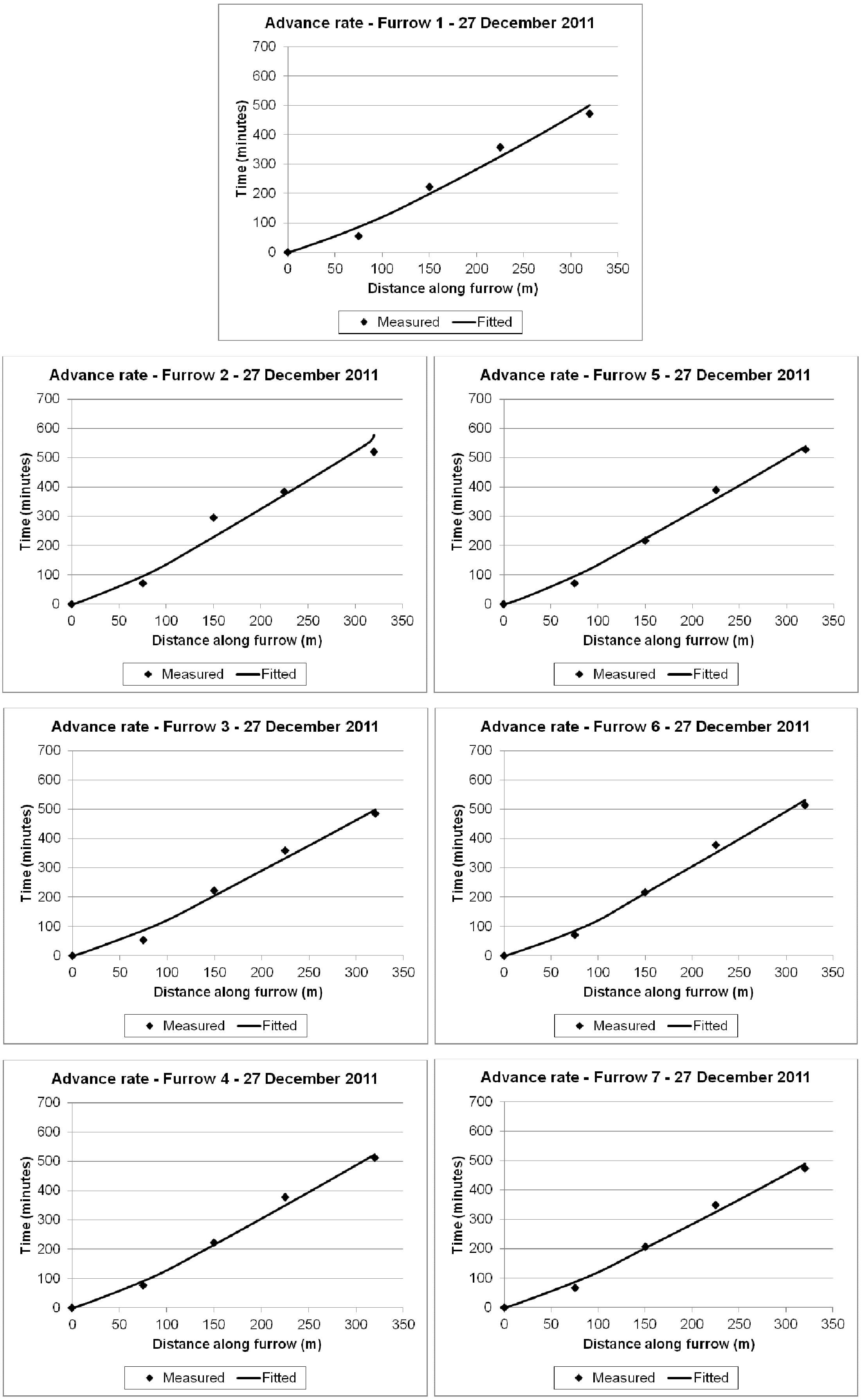


Figure 4.4: Meausred and fitted advance rate measurements for seven furrows

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5. Irrigation application distribution for centre pivot and lateral move irrigation

5.1 INTRODUCTION

The VARIwise control strategies assume that the irrigation volume is applied as desired. However, wind drift and evaporation can distort sprinkler water distribution patterns, leading to either additional water application or irrigation losses of up to 2 to 40% (Ortega et al. 2000). Poor uniformity of irrigation application often contributes to the spatial variability in soil-water and crop yield (Bruckler et al. 2000; Dechmi et al. 2003). The magnitude of the application variation is influenced by both irrigation equipment (e.g. nozzle size, operating pressure) and climate (e.g. temperature, wind velocity) (Yazar 1985; Steiner et al. 1983).

Unmeasured variability in sprinkler irrigation application can affect the performance of site-specific irrigation strategies. Typically irrigation application is measured using catch cans following an irrigation event. However, the wind-affected sprinkler pattern will change temporally and measurement of previous irrigation events will not enable the control strategies to adapt to future irrigation events. Hence, the strategies should consider the uncertainty in the sprinkler irrigation application caused by wind drift and evaporation application during the optimisation process. There are two approaches to achieve this, either:

1. the control strategy determines the optimal irrigation volume as a statistical distribution rather than a real number; or
2. the control strategy incorporates a droplet ballistic model to predict the sprinkler spray pattern and adjust the irrigation volume accordingly.

Predictive sprinkler models have significant sub-field weather data and computational requirements. Therefore an estimation of irrigation application uncertainty would be preferable to predictive sprinkler models for real-time estimation of irrigation application. The most appropriate approach can be determined by evaluating the control strategy performance with irrigation application uncertainty, and with different amounts of wind drift. This will enable the accuracy of irrigation application calculations required by the control strategies to be determined.

5.1.1 Outline

The approaches for estimating irrigation application distributions can be compared in simulation using VARIwise. This section presents an evaluation of the adaptive control strategies on a simulated centre pivot irrigated cotton crop with spatial irrigation application variations according to: (i) statistical distributions; and (ii) sprinkler distributions generated by predictive sprinkler models at different speeds and directions. This will explore whether a ballistic sprinkler model is required to adequately describe irrigation application variations for irrigation management, and the ability of adaptive control strategies to deal with (and adapt to) unmeasured irrigation application variation. Incorporation of the estimated irrigation application uncertainty into the control strategy could sufficiently consider hydraulic variations in irrigation.

5.2 REVIEW OF BALLISTIC SPRINKLER MODELS

In this study the ballistic sprinkler model was required to predict the spatial irrigation pattern for standard sprinkler packges at different wind speeds and directions. The model must provide precise irrigation application at a grid spacing, where the spacing depends on the cell size used in VARIwise. Hence, the model should provide user-defined spacing for irrigation application depths. There must also be a method to overlay and aggregate the patterns to form the irrigation application pattern along the irrigation machine. A model was selected after a review of ballistic sprinkler models for application to irrigation control strategies.

5.2.1 Existing ballistic sprinkler models

Predictive sprinkler models have been developed to estimate the spray patterns of sprinklers with wind at various speeds and directions. Sprinkler models are typically based on ballistic models that assume that the jet from the nozzle breaks up into a pre-defined drop size distribution immediately or at some distance from the nozzle (Smith et al. 2010). These models are often developed to estimate application uniformity of sprinkler packages for irrigation machine design (e.g. nozzle size and spacing), rather than to predict applications at particular points in the field (Smith et al. 2010).

The models are calibrated using measurements of drop size distribution for the particular nozzle (type and size) such that measured and predicted sprinkler patterns match (Smith et al. 2010). Obtaining these data is time consuming and uneconomical, and hence unfeasible for infield implementations of autonomatic irrigation control. Grose et al. (1998) has used fundamental fluid mechanics to model the interaction of the jet with the surrounding air. This approach is computationally intensive and involves simulating the separation of the jet into individual droplets and then determining the ballistics of the individual droplets after their separation from the plume.

An alternative approach to droplet ballistic models involves a statistical description of the droplet size distribution (Smith 1989; Thompson et al. 2000). These models can overlap the patterns along the machine and aggregate the pattern in the travel direction for implementation on a moving boom. This is required for implementation on a centre pivot or lateral move irrigation machine.

Droplet ballistic models developed include Niwasave (Molle et al. 1999), CPIVOT (Ojedo et al. 1993), CPED (Heermann 1990), LATERAL (Kincaid 2000), LMDep (Smith et al. 2003); Sprinkmod (Andrade et al. 1999; 1999a, 1999b) and SIRIAS (Carrion et al. 2001). These models have been validated for a range of sprinkler nozzles and configurations (e.g. Montero et al. 2001). The sprinkler models differ in hydraulic analysis algorithms utilised, spatial resolution of sprinkler distribution, consideration of wind effects and cost of use. A comparison of these models is presented in Table 1 of Smith et al. (2003).

5.2.2 Overlap of fixed sprinkler pattern

The irrigation volumes applied spatially along an irrigation machine can be achieved by overlapping and aggregating individual sprinkler patterns determined by ballistic sprinkler models. Existing models which enable patterm overlap and aggregation are Spacepro (Oliphant 1999); Catch3D (Allen 1996); and mBoss (which can be directly interfaced with SIRIAS, Smith et al. 2003; Foley 2010). From the comparison of sprinkler models in Smith et al. (2003) the model SIRIAS is the only sprinkler model currently available that considers from sprinkler distribution and effects of wind and can be interfaced with software to overlap sprinkler distributions. SIRIAS requires a radial leg pattern for the given sprinkler, nozzle height and pressure.

5.2.3 Discussion of ballistic sprinkler models

Sprinkler models are used to account for the spray pattern of different sprinkler packages under varying environmental conditions (e.g. wind). However, the models require measurements of wind speed and direction along the irrigation machine at different heights from the ground which is not practical in a field implementation. In addition, new wind measurements and the changing orientation of the irrigation machine will require the irrigation adjustment to be nearly continuously updated. This will lead to an increase in the computing requirements potentially beyond the capability of an irrigation machine-mounted processor. Hence, complex sprinkler models are not feasible for on-the-go precision irrigation decisions.

The hydraulic model SIRIAS was used to estimate the amount of water that was being applied along irrigation machines. This model enables wind sprinkler patterns with different speeds and directions to be implemented. The mBoss model is compatible with SIRIAS to aggregate the patterns.

The VARIwise control strategies were updated to consider irrigation application variation. The sensor-based adaptive control strategies inherently incorporate irrigation uncertainty: Iterative Learning Control (ILC) adapts the irrigation volume to any error in predicted response according to the previous irrigation application, whilst Iterative Hill Climbing Control (IHCC) applies the irrigation volume that corresponds to the highest extrapolated performance index. The MPC strategy was updated to incorporate irrigation application uncertainty by applying the median irrigation volume that corresponds to the highest performance index from the tested irrigation application volumes for each cell and irrigation event. Previously, the MPC strategy applied the irrigation volume with the highest performance index and lowest value.

5.3 EVALUATION OF CONTROL STRATEGIES WITH IRRIGATION DISTRIBUTION VARIATION

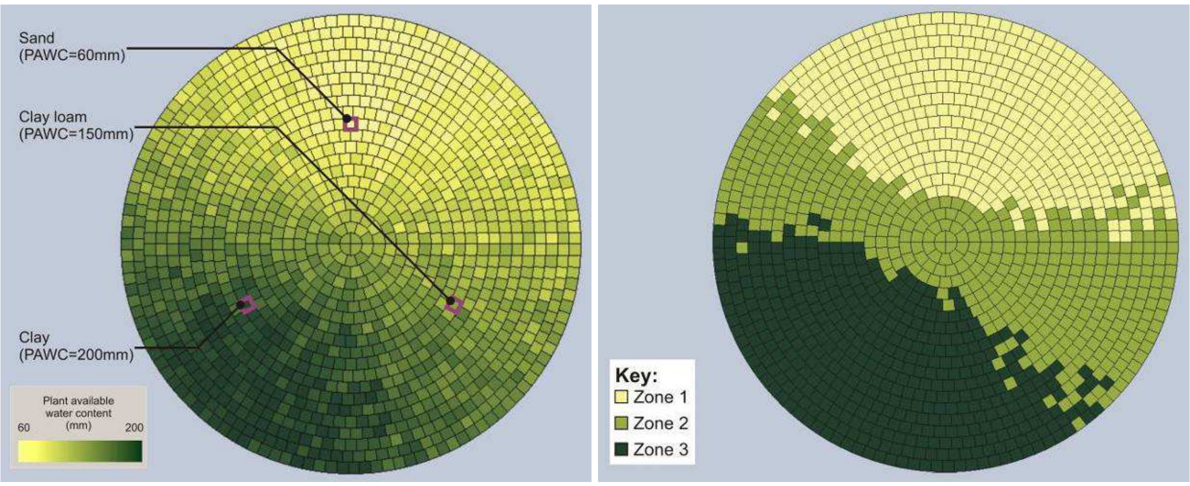
5.3.1 Case study inputs

A simulation case study was conducted to evaluate the performance of the control strategies under different magnitudes of uncertainty in irrigation application. The case study involved simulations of a whole season cotton crop grown on the Darling Downs, Australia with parameters as outlined in Table 5.1. The sowing data, soil properties and weather pattern was characteristic of cotton growing regions in Australia. The soil and plant parameters of the cotton model OZCOT were kept within the boundary values defined by Wells and Hearn (1992).

The spatial variability in soil parameters in each cell for the ILC and IHCC strategies and the zones applied for the IHCC strategy are shown in Figure 5.1. In the simulated field, the plant available water capacity (PAWC) ranges from 60 to 200 mm. This was selected to ensure the control strategies could deal with the different soil types that often exist within fields. For MPC, the field was automatically divided into 44 zones, each of area approximately 0.3 ha (Figure 5.2), and the irrigations occurred daily. This number of zones enabled the simulations to be executed in a timely manner and was appropriate to the substantial in-field spatial variability of soil properties.

Table 5.1: Agronomic factors used in cotton model OZCOT for control strategy simulations (where HydroLOGIC is a user interface for OZCOT, Richards et al. 2008)

Agronomic factor	Value	Source
Sowing data	4 October 2004	Nil
Plant stand	12 plants/m	Default in HydroLOGIC
Seed depth	5 cm	Default in HydroLOGIC
Row spacing	1 m	Default in HydroLOGIC
Available nitrogen	250 kg/ha (for maximum yield)	Rochestor (2006); Rochester et al. (2009)
Previous crop	Other	Nil
Defoliation dates	Determined by OZCOT	Nil
Harvest date	Determined by OZCOT	Nil
Cotton variety	Sicot 73	Nil
Plant available water capacity	As per Figure 1	Nil
Starting soil-water	Plant available water capacity	Nil
Weather data	As per Figure 2	Nil
Machine type	Centre pivot	Nil
Field size	400 m diameter	Nil
Machine capacity	15 mm/day	Nil
End of irrigation period	14 March 2005	Nil



(a) (b)

Figure 5.1: Soil variability for: (a) industry-standard, ILC and IHCC strategy simulation; and (b) the cells assigned to each zone using the soil variability data of Figure 5.1(a)

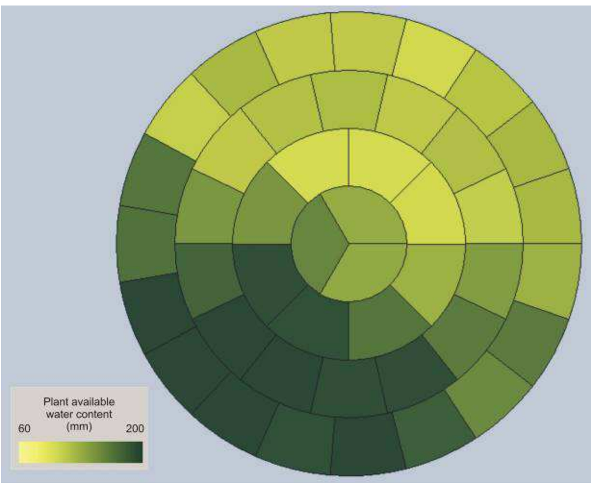


Figure 5.2: Plant available water capacity as calibrated in model predictive control implementation

A daily weather profile was obtained for the GPS location -28.18°N 151.26°E from an Australian Bureau of Meteorology SILO dataset (QNRM 2009) for 2004/2005. The weather profile is relatively hot and wet, late in the crop season (Figure 5.3)

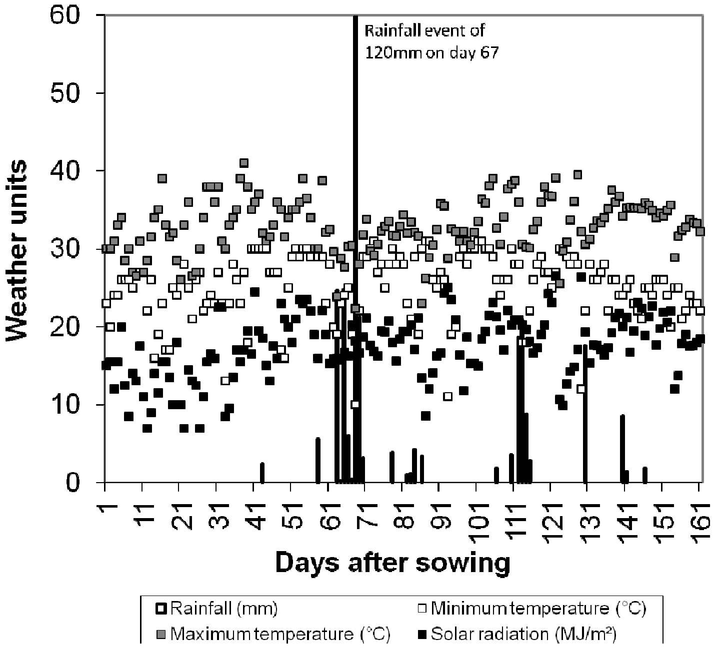


Figure 5.3: Weather profile used in irrigation application variation case study

5.3.2 Irrigation application variation

Methodology – statistical distribution

An uncertainty analysis was conducted in VARIwise for irrigation application using the three adaptive irrigation control strategies (ILC, IHCC and MPC). Ten replicates of simulations were conducted with ±10%, ±20% and ±50% variation in irrigation from each sprinkler during every irrigation event.

Methodology – sprinkler model prediction

Sprinkler distributions from a ballistic sprinkler model were implemented in VARIwise to evaluate the performance of the strategies with different wind strengths. Sprinkler patterns were obtained from the sprinkler model SIRIAS with light wind (0-5 m/s), moderate wind (7.5-12.5 m/s) and strong wind (15-22.5 m/s) and overlapped and aggregated using the mBOSS model at 16 wind directions (0-360° at 22.5° intervals). Ten replicates of the irrigation distribution patterns were generated by randomly selecting and aggregating sprinkler patterns within each strength of wind. For each simulation, a multiplication factor to apply to the irrigation volume for each cell was determined by randomly combining the generated sprinkler patterns. VARIwise control strategy simulations were then conducted using the ten replicates of each wind strength.

5.3.3 Performance of control strategies

Performance of adaptive control strategies with statistical variation in irrigation

The simulated yield and crop water use index of the three adaptive control strategies with different amounts of irrigation uncertainty are shown in Figure 5.4 (full data in Appendix A.1-A.3). These show the impact of uncertainty in irrigation application to be relatively low with ±50% variation 17%, 32% and 21% reduction in yield for ILC, IHCC and MPC, respectively. Hence, the ILC and MPC strategies perform adequately with unmeasured irrigation application uncertainty; however, IHCC performs significantly worse with ±50% variation in irrigation application.

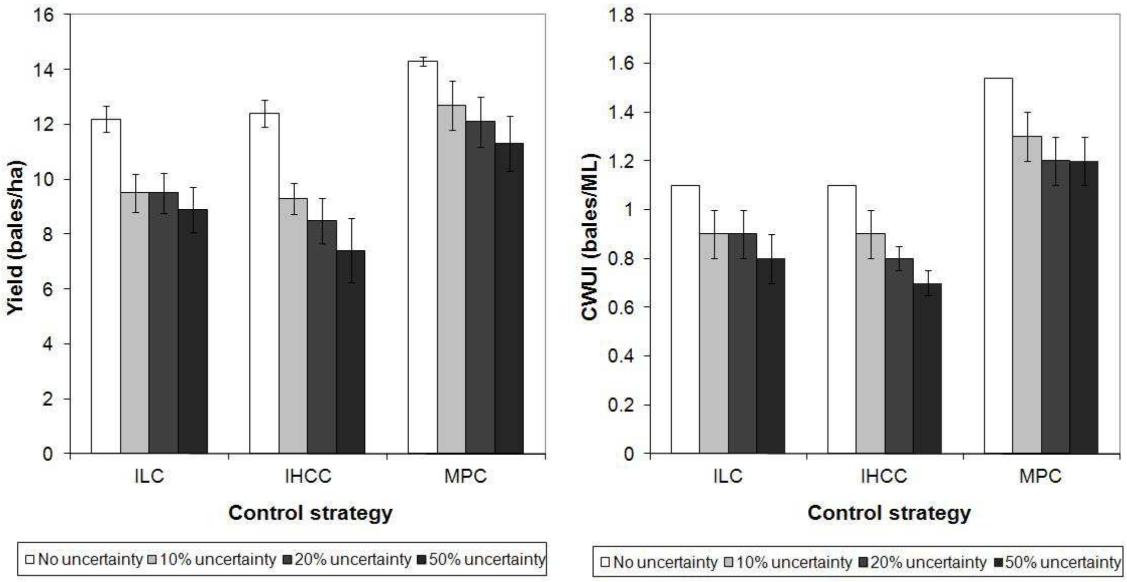


Figure 5.4: Performance of ten replicates of the ILC, IHCC and MPC strategies with irrigation uncertainty of 0%, ±10%, ±20% and ±50% standard deviation

Performance of adaptive control strategies with predictive sprinkler model

Figure 5.5 presents the simulation results for the three adaptive control strategies with ballistic sprinkler patterns predicted using SIRIAS and aggregated using mBOSS at different wind strengths (full data in Appendix A.4-A.6). The results show that the yield can be maintained with light wind, but reduces significantly with strong wind for all control strategies.

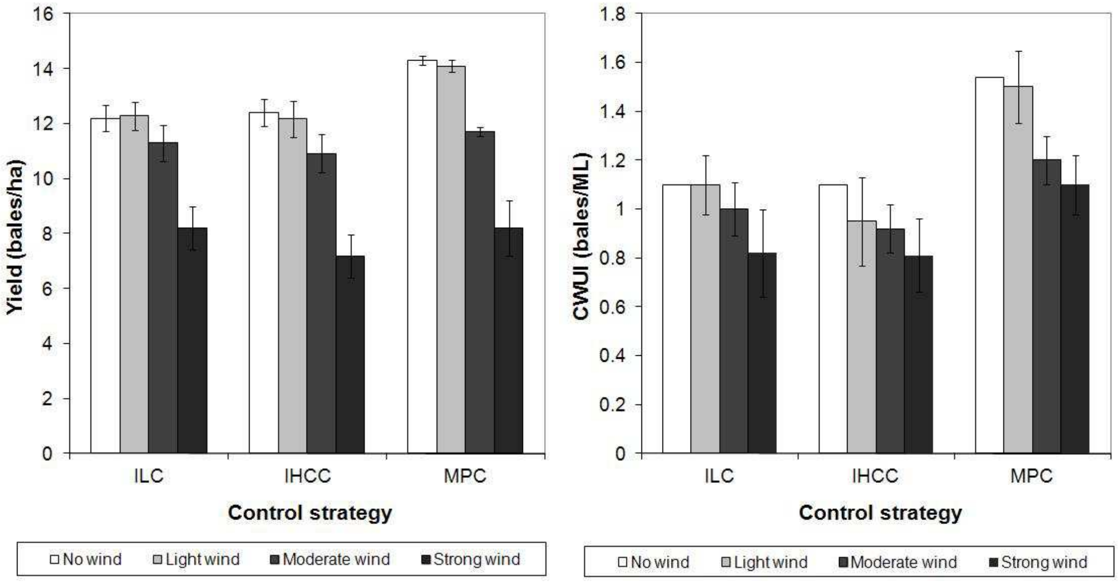


Figure 5.5: Performance of ten replicates of the ILC, IHCC and MPC strategies with light, moderate and strong wind in random wind directions

5.4 VALIDATION OF BALLISTIC SPRINKLER MODEL

The simulations in Section 5.3 showed significant reductions in yield and crop water use index under moderate and strong wind. This indicates that wind could have signifciant impacts on the performance of adaptive control strategies implemented on sprinkler irrigation systems. This also demonstrated that the ability to predict the sprinkler pattern could enable the control strategy to adjust the application accordingly. A validation of the ballistic sprinkler model would enable the accuracy of ballistic sprinkler models to be established. This section describes a field evaluation conducted in 2012/13 that compared the modelled andmeasured sprinkler pattern in different wind conditions.

5.4.1 Methodology

Catch can trials were conducted to evaluate the performance of SIRIAS and mBOSS models at light, moderate and high wind speeds. For each wind strength, catch cans were positioned five metres apart and in three, 10 metre rows (perpendicular to the irrigation machine) under one span of a centre pivot irrigation machine. An individual sprinkler pattern was obtained from the SIRIAS model for a standard sprinkler. The patterns were then overlayed and aggregated using mBOSS with the machine's sprinkler spacing and the measured wind conditions. The wind direction entered into mBOSS was adjusted to account for the irrigation machine's direction of travel. Negative wind directions resulted in the mBOSS output sprinkler pattern being mirrored.

5.4.2 Case study inputs

Catch can trials were conducted during irrigation events on 24 October 2012 (light wind), 10 January 2013 (high wind) and 14 May 2013 (moderate wind), where 20 mm, 15 mm and 20 mm were applied, respectively. One span of a centre pivot irrigation machine in Jondaryan, QLD was monitored. There were fifteen outlets on the span with size 32 3TN nozzles spaced three metres apart. Wind speed and direction were measured using an onsite Weathermaster 2000 automatic weather station (Environdata Australia Pty Ltd., Warwick QLD). Table 5.2 presents the parameters measured using the weather station for input to the sprinkler models.

Table 5.2: Data inputs to mBOSS for sprinkler patterns in light, moderate and strong wind

Parameter	Light wind	Moderate wind	Strong wind
Wind speed (m/s)	3.6	8.9	12.5
Wind direction (°)	10	280	100
Irrigation machine travel direction (°)	330	270	200
Wind direction relative to machine (°)	40	10	-70

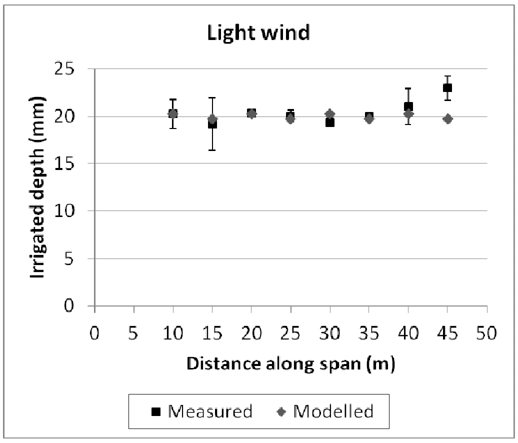
5.4.3 Results and discussion

The results of the catch can trials and corresponding modelled irrigation application distributions are shown in Figure 5.6. There was an average standard deviation of ±1.1, 1.5 and 2.3 mm in the measured irrigation volumes along the irrigation machine at the light, moderate and strong wind speeds, respectively.

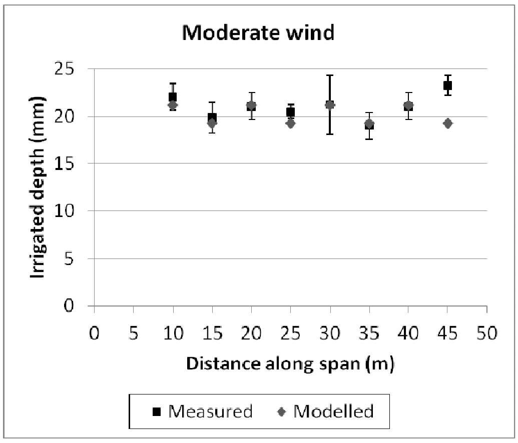
The measured irrigation depths along the span generally followed the predicted irrigation patterns for light and moderate wind. The predicted irrigation depths were generally within the range of measured irrigation depths.

These results indicate that a predictive ballistic sprinkler model could estimate the sprinkler patterns at three wind speeds. Incorporation of a sprinkler model to adjust the irrigation could improve the performance of adaptive control strategies. However, this would require localised wind sensors which may not be feasible in a commercial field situation.

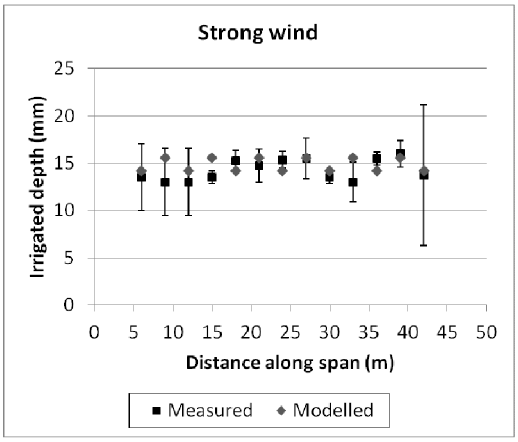
The adaptive control strategies assume that the optimised irrigation volume is applied as desired. The estimated variation in irrigation depths caused by wind could be used to update the crop model utilised by the control strategies following each irrigation event to improve the model accuracy. A further enhancement may involve using the predicted irrigation patterns to adjust the optimal irrigation application as determined by the adaptive control strategy to account for the predicted variation caused by the wind. However, this approach is computationally complex and would not be feasible in the scope of this project. Final yield can be maintained if irrigation is applied under low speed wind and as the uniformity of irrigation is not significantly influenced by wind drift and evaporation in this situation.



(a)



(b)



(c)

Figure 5.6: Comparison of measured and modelled sprinkler patterns in: (a) light wind; (b) moderate wind; and (c) strong wind

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6. Irrigation control hardware for field evaluations

6.1 CONTROL HARDWARE REQUIREMENTS

Field evaluation of the adaptive irrigation control strategies required variable-rate control hardware to adjust the irrigation application and/or timing. These trials were conducted on a section of the field rather than on an entire irrigation system (e.g. irrigation machine). Hence, the flow adjustment and monitoring hardware requirements were modest.

The control hardware had to be interfaced with VARIwise to receive the irrigation adjustment signals either at a set time (for surface irrigation) or irrigation machine position (for overhead irrigation). A web-enabled system was required to enable real-time updates to the irrigation adjustments. Remote access to the irrigation controller would also allow remote monitoring of the irrigation system performance.

6.2 COMMERCIALLY AVAILABLE CONTROL HARDWARE

6.2.1 Surface irrigation

The majority of surface irrigation systems in Australian cotton do not use automation to commence, end or control irrigation application during events. Site-specific surface irrigation potentially enables the variability of crop water requirements in the field to be accounted for. However, growers often manually change irrigation application where there are large areas of the field with different soil or infiltration properties. This is often achieved for irrigation machines by adjusting the machine speed; and for surface irrigation by changing flow rate into individual furrows with different siphon sizes or adjusting the outlets of gated pipe.

Commercially available hardware that enables surface irrigation automation consists of channel and outlet gates fixed to concrete structures controlled by electromechanical actuators (e.g. Rubicon SlipGate, FlumeGate) or mechanical timers (e.g. Padman Stops). This technology is presently limited to on-farm flow control. A review of commercially available channel and outlet gates can be found in Koech et al. (2010). However, there is no commercially available automation hardware for the most common methods of surface irrigation used in the Australian cotton industry (siphon; gated pipe; bank-less systems; and pipes through banks). Control hardware has been developed in research to regulate inflow rate through individual outlets of a delivery manifold using diaphragm valves driven by rotary actuators (Hibbs et al. 1992).

6.2.2 Centre pivot and lateral move irrigation

Existing commercial variable-rate irrigation systems for centre pivots and lateral moves are manufactured by Design Feats (formerly Farmscan), Valmont Irrigation and Precision Irrigation. Either individual or groups of sprinklers are pulsed and off using solenoid valves to create time-proportional control. The valves are powered electrically or pneumatically and in groups of sprinklers (Design Feats, Valmont Irrigation) or individually (Precision Irrigation). The Design Feats and Valmont Irrigation systems allow adjustment of the irrigation application at increments of 1° around the field, whilst the Precision Irrigation system allows an infinite number of adjustments around the field. The Precision Irrigation system is Internet-enabled and uses wireless communication to control the valves. Currently only two commercial growers in Queensland are known to have variable-rate irrigation hardware installed on a centre pivot/lateral move irrigation machine: a sugarcane field in Mackay (Wigginton, DW 2011, pers. comm., 12 April) and a dairy field in Thornton (a field site used for a SEQ IF project at the NCEA). These commercial systems can also achieve variable application volumes to a limited extent by varying the speed of the LMIM. This approach does not vary the irrigation application along the length of the lateral; rather, it varies the irrigation application only in the traverse direction.

Solenoid-based applicators have been developed and implemented in research applications (Perry et al. 2003; Evans et al. 1996; Han et al. 2009; Bradbury and Ricketts 2009). Two other approaches to variable-rate irrigation for centre pivots and lateral moves have used: (i) multiple manifolds of different-sized nozzles in combinations to create a stepwise range of rates (King and Wall 2005; Sadler et al. 2002); and (ii) a concentric pin inserted into the sprinkler nozzle to reduce the cross sectional area of the nozzle, where the pin is then cycled in and out with the duty cycle required to achieve the desired time-averaged flow rate (King and Kincaid 1996; King et al. 1997).

Following discussions with the commercial variable-rate providers, Design Feats offered their variable-rate irrigation systems at cost, whilst Precision Irrigation offered their variable-rate irrigation system for loan. This avenue will be pursued for whole field evaluations of variable-rate irrigation, rather than a modest field evaluation.

6.3 CONTROL HARDWARE DEVELOPMENT

Automated control hardware was specifically developed for the surface and overhead pressurised irrigation evaluation (Figure 6.1). This involved additional hardware installed in-line with the irrigation outlets (Figure 6.2). The basis for the approach was flow control and used the following components:

- **Ball valve for flow control**
  Each irrigation outlet was fitted with a brass ball valve (50 mm for siphons, 20 mm for overhead outlets). The ball in each valve was altered such that there was no sharp-edged orifice and was effectively a linear flow controller. The inlet was designed to plug directly in-line with either the siphon for surface irrigation or the dropper for overhead irrigation system. For the overhead irrigation system, the outlet connection also enabled connection to the sprinkler head.
- **Servomechanism for flow adjustment**
  A servo was used to adjust the flow through the ball valve. This was implemented using a linkage between the servo arm and the ball valve arm.
- **Flow meter**
  A flow meter was installed after each ball valve and produced a pulse output for every ten litres that passed through the meter.
- **Irrigation control board to interpret signals**
  A microcontroller board was required for each irrigation outlet to individually receive control signals from the main controller and transmit flow meter readings to the main controller. The power and data transmission was provided to each irrigation control board from the main controller using wires along the head ditch or main pipe of the irrigation machine.
- **Main controller**
  A mini-computer was used as the main controller for the irrigation hardware (Fit-PC2, CompuLab, Israel). A microcontroller board sent control signals to and received flow readings from the irrigation control boards. The computer was connected to the Internet, accessed online files on a FTP server and transmitted servo positions to the irrigation control boards as appropriate. A GPS was also connected to the microcontroller board for time and position information. The computer turned on when flow was detected from a meter and during set times of the day for maintenance.
- **Data processor**
  A remote data processor processed the infield data and updated files on a server containing the control signals and corresponding time and/or position in the field. This processor executed VARIwise to determine the irrigation application and accounted for the irrigation system hydraulics to determine the appropriate control signals.

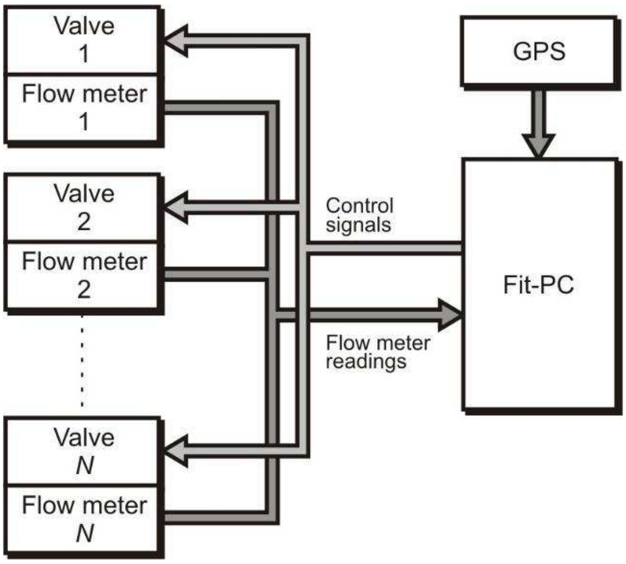

Figure 6.1: Hardware used to measure and adjust irrigation application

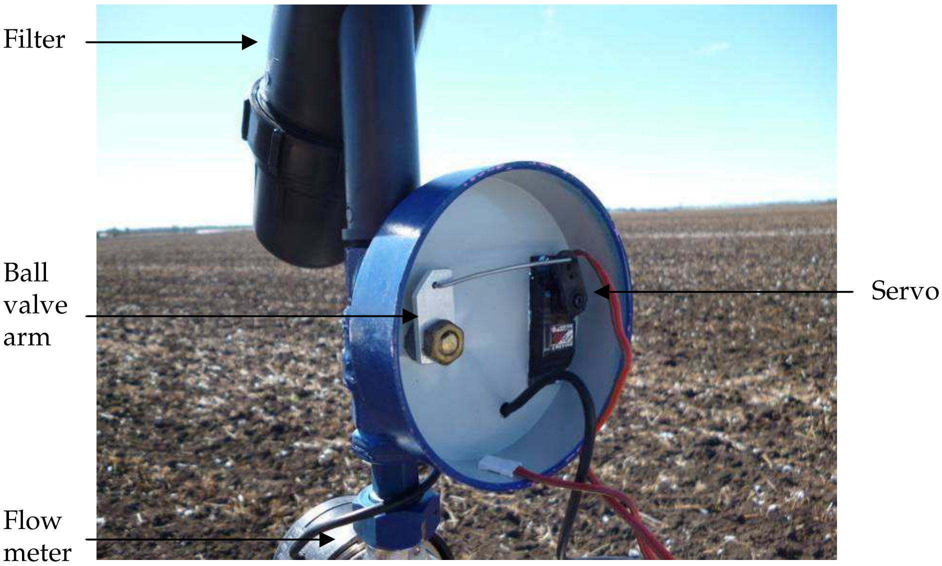

Figure 6.2: Hardware used for adjusting flow rate during irrigation events

6.4 CONTROL HARDWARE – SURFACE IRRIGATION

6.4.1 Surface irrigation automation

The advance rate is required for determine irrigation infiltration and traditionally measured using contact sensors at different distances along the furrows. Alternate advance rate sensing systems have also been developed. For example, cameras can be used to capture images of the advance front and analysed to estimate current position of advance front (Lam et al. 2006, McCarthy 2004). The machine vision system was found to be accurate for short distances (i.e. less than 76 m from the head ditch), but there was significant loss of accuracy for long furrows of about 400 m long. To ensure the accuracy of the advance meters at all distances along the furrow, contact sensors were developed and installed at four locations along each controlled furrow. These sensors detected the advance front by measuring the resistance across two exposed wires and a wireless signal was transmitted to a base station at the head ditch when the resistance was above a set threshold (Figure 6.3(b)). When water was detected, a wireless signal was transmitted to a receiver on the main controller using a remote control.

Ultrasonic flow meters selected for the siphons to minimise impedance on flow rate (Octave ultrasonic flow meters, Arad Group, Israel). These were designed such that the siphon could directly plugged into the control hardware.

The flow rate through the siphons was automatically and remotely adjusted with valves in-line with the siphons which changed the diameter of the siphon outlet, and in turn altered the flow rate (Figure 6.3(a)). The adjustment control signal transmitted to the control valve was determined using a common Iterative Learning Control algorithm (Ahn et al. 2007) which calculates the required system input (the irrigation adjustment to be applied) u_k at the current iteration, i.e. the (k)-th irrigation, according to

$$u_k(t) = u_{k-1}(t) + \gamma(y_k(t) - y_d(t)) \qquad (6.1)$$

where:

u_k	=	the system input (the irrigation adjustment to be applied) on the current valve update (k-th adjustment iteration)
γ	=	the learning gain
$y_k(\Delta)$	=	the *measured* system output (i.e. measured advance distance along furrow); and
$y_d(\Delta)$	=	the *desired* system output (i.e. *desired* advance distance along furrow).

The learning gain γ was chosen to be 2 by iteration as a compromise between slow learning (low γ) and instability in the predicted u_k values (high γ).

(a) (b)

Figure 6.3: (a) Inflow meters installed in-line with siphons; and (b) advance meter

6.4.2 Validation of irrigation application – surface irrigation

Six siphon control valves were developed and used in irrigation trials on 11 January 2012 and 6 February 2012. The implemented irrigation adjustment and measured flow rate were compared during the trial on 11 January 2012 to evaluate the performance of the surface irrigation control hardware (Figure 6.4). The flow depended on the head and water supply; hence, the measurements used in this comparison were taken while the head was constant.

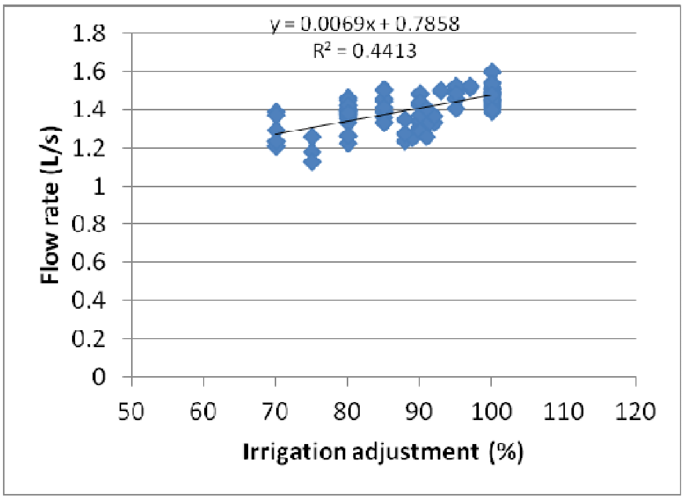

Figure 6.4: Comparison of measured flow rate and desired irrigation adjustment for six siphons

From Figure 6.4 there was a linear relationship between the percentage irrigation flow adjustment and measured flow rate. There were variations in flow rate produced by the irrigation adjustment across the seven furrows. This was likely caused by slightly different heads between the siphons and temporal changes in head throughout the irrigation event causing the overall flow rate to change.

6.5 CONTROL HARDWARE – OVERHEAD IRRIGATION

6.5.1 Overhead irrigation automation

Fifteen in-line filters, flow control valves and flow meters were installed on one span of a centre pivot irrigation machine (Figure 6.5). The filters were used to prevent flow valve blockages from debris in the water and single-jet inferential (mechanical) 15 mm flow meters (FluidFlo, Australia) were used. The internal filter was removed from each flow meter to reduce blockages as an external filter was used.

Figure 6.5: Water filter, flow meter and controllable ball valve on outlet of centre pivot irrigation machine

A remotely accessible user interface for the control hardware and measurements was developed (Figure 6.6). The software was used to manually update the variable-rate irrigation control signals as required. The user interface also enabled the monitoring of flow rates from each outlet, position tracking of the irrigation machine, and camera surveillance of the span. LogMeIn software (https://secure.logmein.com/) was installed for remote desktop access and control. DropBox file sharing software was used to transfer files containing the irrigation control signals between the remote processor that determine irrigation volumes and the infield main controller computer.

6.5.2 Validation of irrigation application – overhead irrigation

The flow rate measurements were recorded during each irrigation event during the crop season. This enabled a comparison of the irrigation application adjustment with the flow rates measured using flow meters to ensure that the irrigation application from the outlets was correct (Figure 6.7). There was a linear relationship between the measured flow rate and the percentage irrigation adjustment. Variations in the flow rate at set percentage irrigation adjustments were likely caused by slight blockages in the outlets.

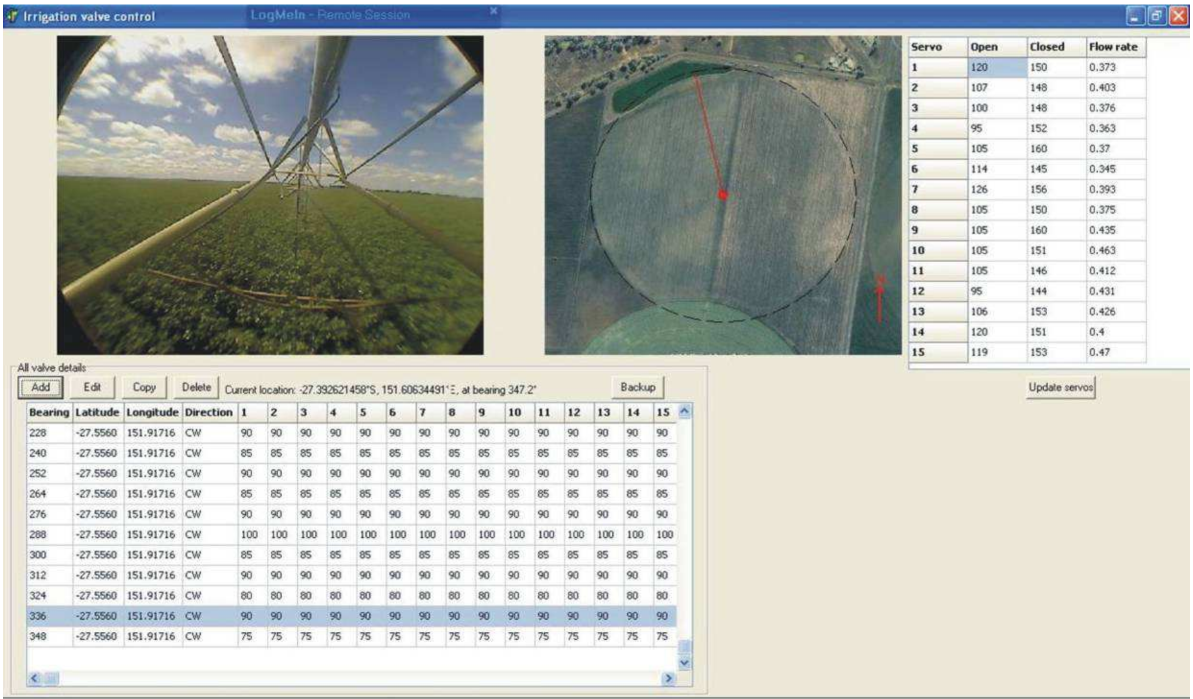

Figure 6.6: Real-time, remote control and monitoring of irrigation hardware with camera viewing span and position of centre pivot irrigation machine

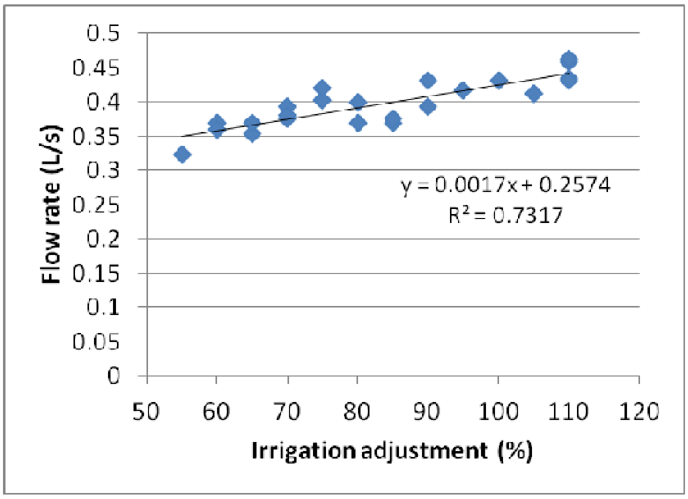

Figure 6.7: Comparison of measured flow rate and desired irrigation adjustment on one span of centre pivot irrigation machine

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7. VARIwise for optimisation of seasonal cotton management of surface irrigation

7.1 INTRODUCTION

Over 94% of irrigated cotton in Australia is grown using surface irrigation (Raine and Foley 2002), a gravity method of irrigation. Surface irrigation has low energy consumption and initial capital cost, but typically uses 30-40% more water and is more labour intensive than centre pivot and lateral move irrigation systems (DAFF 2006). Surface irrigation systems apply water with 50-90% efficiency, whilst centre pivot and lateral move irrigation machines apply water with 80-95% efficiency (VDPI 2011). This is because surface irrigation systems convey water into furrows or bays which flows down sloped fields; hence the inflow is typically continuous until the advance front reaches the end of the field. In contrast, centre pivot and lateral move irrigation machines traverse the field and apply irrigation water directly to the crop under the irrigation machine.

The utilisation of automation and optimisation of surface irrigation can reduce labour and provide water savings. The predominant method of surface irrigation in Australian cotton uses siphons that are manually primed to start irrigation and stop irrigation. The control valves installed on siphons as described in Section 6.4 would enable the control of flow rate and cut-off time. Optimisation algorithms are required to determine the irrigation adjustments.

Optimisation algorithms have been developed to refine irrigation application for surface irrigation systems and applied through adjusting one or a combination of the following: (i) day of the irrigation event; (ii) inflow rate; and/or (iii) cut-off time. For option (i), the day of the irrigation event is typically determined by the soil-water deficit and crop stage. Optimisation algorithms (e.g. genetic algorithms) have been applied to determine surface irrigation timing (Schmitz et al. 2007).

Algorithms have been developed to refine the inflow rate and/or cut-off time (options (ii) and (iii)) such that the irrigation inflow is turned off before the advance front reaches the end of the furrow, but the slope of the field and infiltration characteristics enable the advance front to still reach the end of the furrow. Optimal inflow rates and cut-off times can be determined from surface irrigation models that estimate the infiltration trajectory (e.g. ‘SISCO’ Gillies et al. 2010; ‘WinSRFR’ Bautista et al. 2009; ‘HYDRUS-2’ Wöhling et al. 2006), and adjusted either once before the irrigation event from historical data or estimation (e.g. Khatri and

Smith 2006; Koech et al. 2010), or throughout irrigation events from real-time advance rate measurements (e.g. Clemmens and Keats 1992; Hibbs et al. 1992). The basis for these is typically a surface irrigation hydraulic model, developed from flow models to determine the wetting profiles along the field.

The surface irrigation models determine infiltration parameters that characterise the movement of irrigation along the furrow, and estimate the distribution of irrigation infiltration along the field using historical flow rate and advance rate measurements and cut-off time. However, they do not consider plant and soil response to irrigation and the infiltration distribution selected only using the surface irrigation model may not necessarily maximise yield or water productivity of the crop. An alternate approach is to develop the desired infiltration distribution by considering the spatial variability of crop water requirements along each furrow. The inflow rate and/or cut-off time could then be adjusted to best achieve the desired variability. Crop water use models have been incorporated into the optimisation of inflow rate and cut-off time using neural networks and dynamic programming (Wöhling and Schmitz 2007; Wöhling and Mailhol 2007); however, these were simplified crop models that did not consider structural and fruiting development for specific crops.

Adaptive control strategies developed as part of the 'VARIwise' control framework (McCarthy et al. 2010) can incorporate weather, soil and plant sensor inputs to determine irrigation application and/or timing. The capability to determine the inflow rate and cut-off time that produces an irrigation distribution along furrows that was closest to the optimal irrigation distribution was incorporated into VARIwise (described in Section 4.2).

7.1.1 Outline

This section describes the application of site-specific adaptive control strategies to surface irrigation. This involved the adaptation of the VARIwise framework to surface irrigation, and the setup and results of a field trial demonstrating these control strategies. These are described by:

- collection of field measurements for trial to evaluate the real-time adaptive control of surface irrigation (Section 7.2)
- processing of field data into correct format for control strategy implementation (Section 7.3)
- comparison of results of the irrigation control strategies (Section 7.4)

7.2 MATERIALS AND METHODS

7.2.1 Field site

Sicot 74BRF was planted on a siphon irrigated site at Jondaryan, Queensland (with GPS location 27°24'34.33" S 151°36'8.00" E) on 25 October 2011. The rows were 318 m long, furrow spacing was 1 m, field slope was 0.0016011 m/m and each siphon irrigated two rows of cotton. Urea was broadcast on the cotton crop on 19 December 2011 and the soil nitrogen content was estimated to be 150 kg/ha by the farm's agronomist.

The topography of the field was measured using a dumpy level on 19 September 2011 for input into the hydraulic model and to choose a trial area with a slope as close to constant as possible. A vertical EM survey was conducted on the field on 23 September 2011 to estimate the variability of the soil properties (Figure 7.1). This EM survey indicated increased clay content in the soil at the centre of the furrows (Figure 7.2).

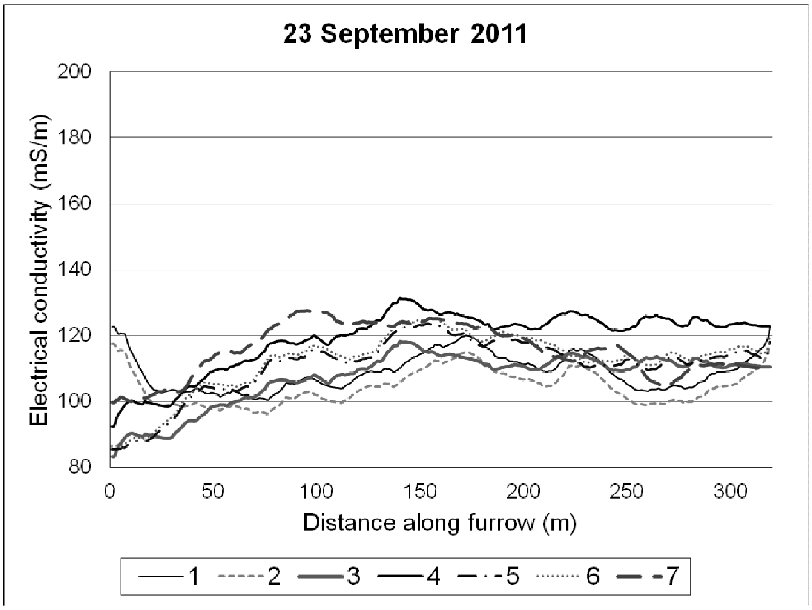


Figure 7.1: Measured electrical conductivity along seven furrows at trial site to evaluate spatial variability of soil properties

7.2.2 Adaptive control strategies

The strategies implemented in VARIwise are based on advanced process control that have been identified as being applicable to improve irrigation management to refine the irrigation application and timing (McCarthy et al. 2013). Such control strategies take an engineering approach and are now routinely applied for manufacturing and chemical process systems and combines elements from many disciplines spanning classical control engineering, signal processing, statistics, decision theory and artificial intelligence (Ikonen and Najim 2002).

Two types of strategies have been identified for implementation in irrigation control: (a) sensor-based strategies which determine the irrigation application directly from field measurements (i.e. to fill soil profile); and (b) model-based strategies which determine irrigation application from a crop model calibrated using field measurements. For example, Iterative Learning Control (ILC) involves refining system inputs using the error between a measured and desired soil and/or crop response (e.g. soil-water). Model Predictive Control (MPC) executes a model repeatedly to determine irrigation volume and timing that achieves the desired performance objective.

Sensor-based control strategies require iterations of irrigation events to adapt the irrigation application throughout the crop season. However, surface irrigation events are not frequent (typically a maximum of five irrigations within a cotton season), and would be insufficient for sensor-based strategies to sufficiently refine the irrigation application. Model-based control strategies are applicable to surface irrigation because the model calibrated using the available data can effectively update the decision rather than requiring an irrigation event to update the algorithm. Hence, the model-based strategy MPC was evaluated for real-time adaptive control of surface irrigation.

Two replicates of the MPC treatments were implemented with three different objectives: (i) to fill the soil profile; (ii) to maximise yield; and (iii) to maximise crop water use index (Table 7.1). Six furrows were sensed and controlled and an additional furrow was monitored (but not controlled) for comparison. The optimal irrigation distribution along each furrow was derived using VARIwise with the available input data.

Table 7.1: Irrigation control strategies implemented on seven furrows of trial

Furrow	Performance objective	Replicate
1	N/A	1
2	Fill soil-water profile	1
3	Maximise yield	2
4	Maximise CWUI	3
5	Fill soil-water profile	1
6	Maximise yield	2
7	Maximise CWUI	3

7.2.3 Surface irrigation hydraulics

To simulate surface irrigation events, the infiltration parameters of each furrow were determined from an irrigation event on 27 December 2011 using irrigation measurements and the surface irrigation simulation model (a process described in Section 4). This required collection of inflow rates through each siphon using Octave ultrasonic flow meters (Arad Group, Israel) and advance rate using four advance sensors along each furrow (Section 4). The measured flow and advance rates were recorded to an on-site Fit-PC2 computer (Compulab, Israel) with a timestamp. For this trial, the cut-off time was fixed according to the optimised irrigation parameters before the irrigation event, whilst the flow rate was adjusted according to the difference between the measured and optimal advance trajectory.

7.2.4 Measurements

Weather, soil-water and plant data were collected between November 2011 and March 2012. These were used to calibrate the cotton model OZCOT within VARIwise following the procedure of McCarthy et al. (2011). The field trial was divided into 448 cells where the cells were 2 m (two furrows) wide and 5 m long (64 cells along each pair of furrows). A Weathermaster 2000 automatic weather station (Environdata Australia Pty Ltd., Warwick QLD) was installed in the field of the trial area (Figure 7.2).

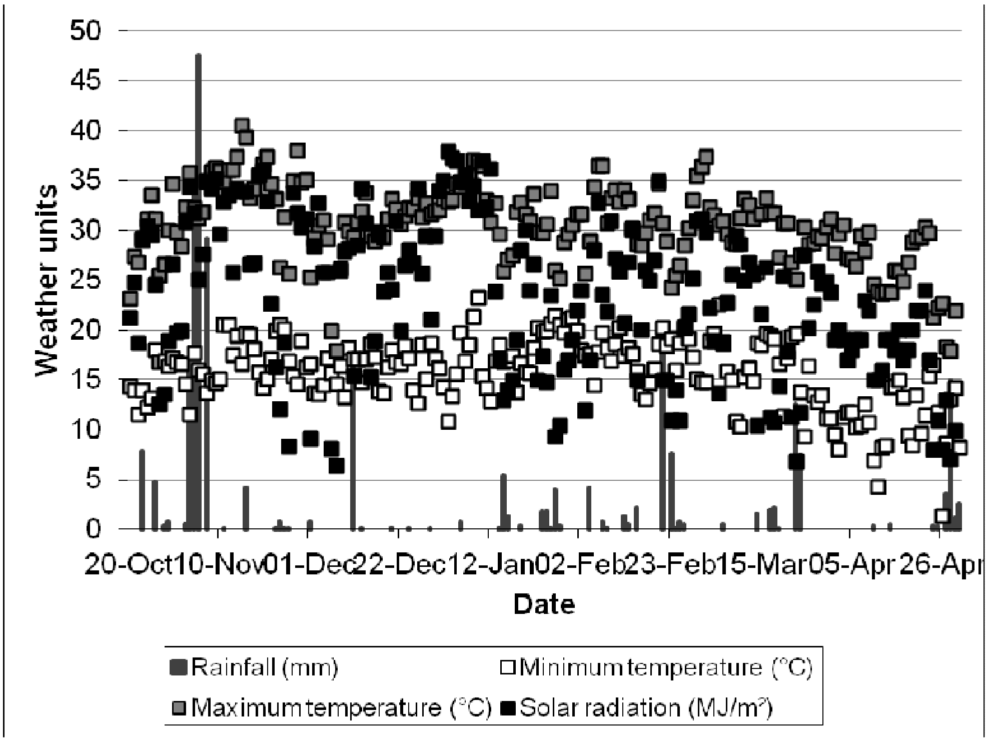


Figure 7.2: Weather data during trial for Adelong farm in Jondaryan, Queensland

ICT International MP406 standing wave soil-water sensors were installed at the centre of each furrow at three depths (30 cm, 60 cm and 90 cm) and measure volumetric soil-water (%) on 7 November 2011 after the cotton had germinated. The electromagnetic induction of the soil was measured to estimate spatial variability of soil characteristics by manually carrying the sensor over the field before and after each irrigation event. Plant density, plant height (to estimate leaf area index), boll counts and flower counts (to estimate square counts) were sensed using the ground-based fruit load and vegetation sensing system described in Section 2. Plant measurements were manually collected at the centre of the seven furrows on each measurement date for comparison (Section 2).

7.2.5 Data processing

The soil-water sensors measured volumetric soil-water (%); however, the OZCOT model requires soil-water measurements in millimetres for calibration. The soil-water sensor data were converted to soil-water (mm) by comparing the apparent change in volumetric soil-water with known soil characteristics (plant available water capacity as determined by agronomist and daily crop water use).

Direct measurement of soil-water using infield sensors at a high spatial resolution is not practical or feasible in a commercial cropping situation. A common non-contact soil sensor is based on electromagnetic induction (EM). EM measurements have been correlated to soil-water measurements (Hossain 2008); hence, following each survey these measurements were correlated to the soil-water measurements to estimate the spatial variability of soil-water.

7.3 FIELD DATA AND PROCESSING

7.3.1 Soil data

Soil-water readings were collected between November 2011 and March 2012. These required conversion from volumetric soil-water content (%) to soil-water (mm). This was achieved by monitoring the apparent soil-water change during rainfall events of 4 mm on 16 November 2011 and 18 mm on 11 December 2011 and the pre-watering irrigation event on 27 December 2011. The measurement difference was compared with the measured irrigation/rainfall depth (Figure 7.3) to determine the calibration equation for the soil-water change (first row of Table 7.2).

This adjustment accounts for the relative changes in soil-water throughout the crop season, but does not account for the quantitative soil-water values with respect to the field capacity and refill point of the soil. Hence, the soil moisture curves were also adjusted such that the maximum soil-water until the first controlled irrigation event aligned with the soil field capacity. In this fieldwork, the maximum field capacity in the trial was taken to be 185 mm (as determined by the farm's agronomist) and the soil-water readings were adjusted accordingly (Figure 7.3). The plant available water capacity was then estimated in the seven cells with soil-water sensors to be the maximum adjusted soil-water reading before the first controlled irrigation event.

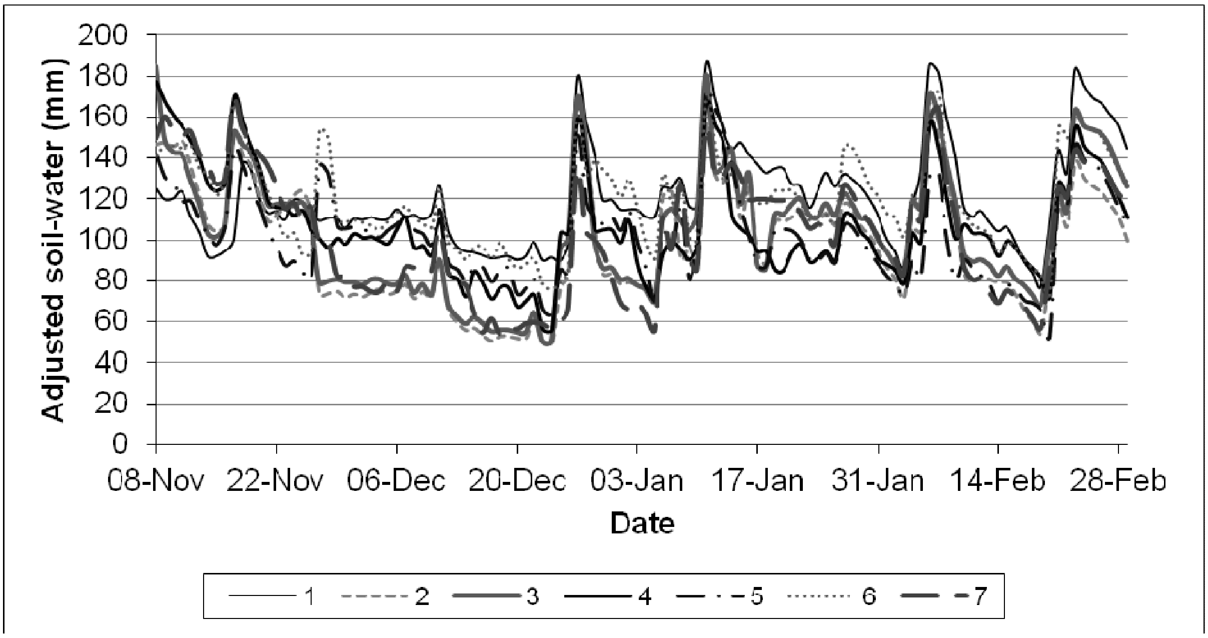


Figure 7.3: Volumetric soil-water measured daily at the centre of each furrow

EM measurements were used throughout the cotton season to estimate the spatial variability of plant available water capacity and soil-water in the unmeasured cells. Linear regression equations were developed for the seven cells with soil-water sensors on each measurement day for the relationships between EM and plant available water capacity, and EM and sensor-measured soil-water (Table 7.2). These regression equations were used to estimate soil properties and soil-water in the unmeasured cells of the field (Figure 7.4).

Table 7.2: Estimation of the plant available water capacity and soil-water using field measurements

Date	Measurement (y)	Sensor input (x)	Regression	Goodness of fit
16 November, 10, 27 December 2011	Change in soil-water depth	Change in sensed soil-water	$y = 11.482x - 0.6078$	0.9629
13 October 2011	Plant available water capacity	EM	$y = 2.4118x - 162.24$	0.8751
10 November 2011	Soil-water	EM	$y = 1.037x - 13.327$	0.3397
13 December 2011	Soil-water	EM	$y = 1.1368x - 108.85$	0.4718
7 January 2012	Soil-water	EM	$y = 1.6209x - 138.99$	0.2896
21 January 2012	Soil-water	EM	$y = 2.3261x - 270.24$	0.3113

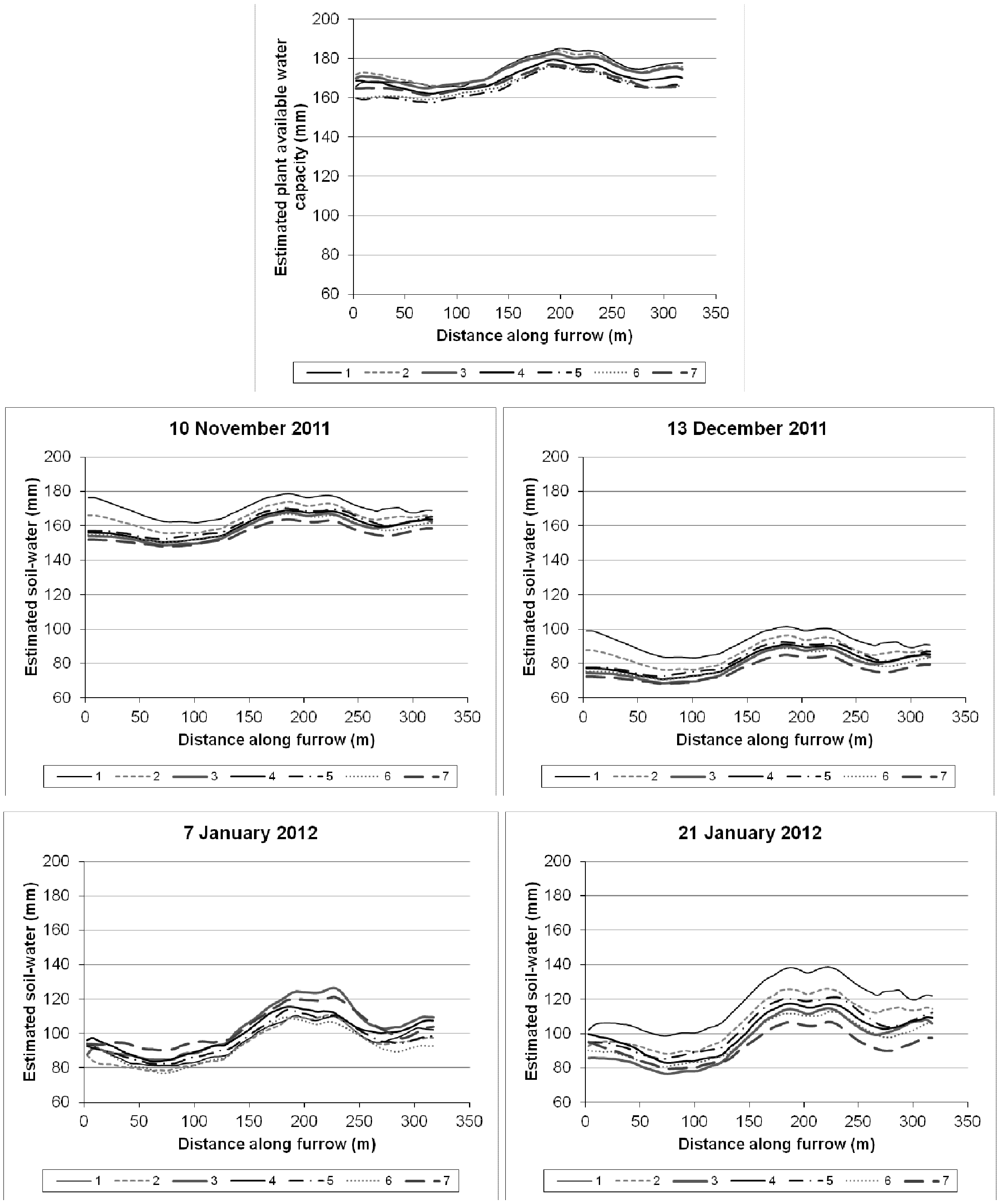


Figure 7.4: Estimated plant available water capacity and soil-water along the seven furrows using point soil-water and EM measurements

The plant available water capacity was highest at 200 m along the furrow for all furrows in the trial and overall highest in the uncontrolled furrow. The spatial variation in plant available water capacity was low at 5.6 mm across the field.

On all measurement days the soil-water was lowest at about 70 m into the furrows and the tail drain which corresponds to the areas with lower plant available water capacities. There was a soil-water peak about 120 m along the furrows. There was more variability in soil-water along each furrow as the season progressed (with average standard deviations along the furrows of 5.8 mm, 6.3 mm, 10.7 mm and 12.1 mm for the four measurement days). The soil-water was higher in the uncontrolled furrow (furrow 1) than the other furrows.

7.3.2 Plant data

Plant measurements were taken on 30 November 2011, 19 December 2011, 7 January 2012 and 21 January 2012 using the ground-based plant sensing system (described in Section 2). Field access to take measurements was limited in early 2012 because of rain and irrigation events.

Plant density

Plant density was estimated along the seven furrows on 10 November 2011 and on average was 9.2 plants/m² (Figure 7.5). The variation in the plant density along the furrows was caused by gaps in the cotton planting. There was no apparent spatial pattern in plant density along the furrows.

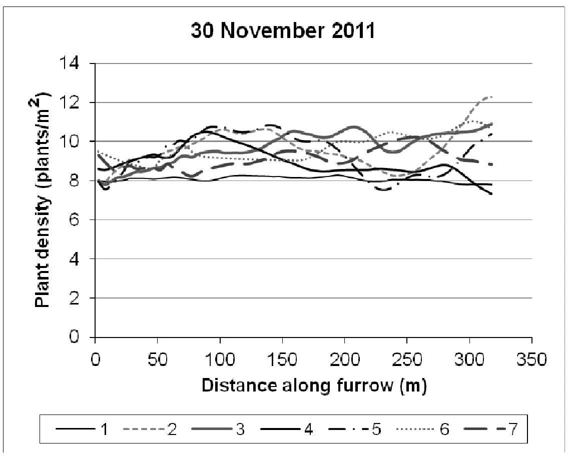


Figure 7.5: Plant density estimated using plant sensing system along seven furrows in trial

Plant height

Plant height was measured along each furrow using an ultrasonic distance sensor (Figure 7.6). The plants were generally taller at the tail drain end than the head ditch end. This is likely because more irrigation water was applied at the head ditch which may have reduced vegetative growth if over-watered.

The plant height became more variable along the furrows as the crop season progressed; however, there was only a small variation in plant height along the furrows (± 2.9%). On all measurement days, the plants under the MPC strategy to maximise yield (furrows 3 and 6) were the tallest (which also contained the lower plant available water capacity and soil-water). On 7 January 2012 and 21 January 2012 the plant height in furrow 1 (uncontrolled furrow) was the lowest in the trial.

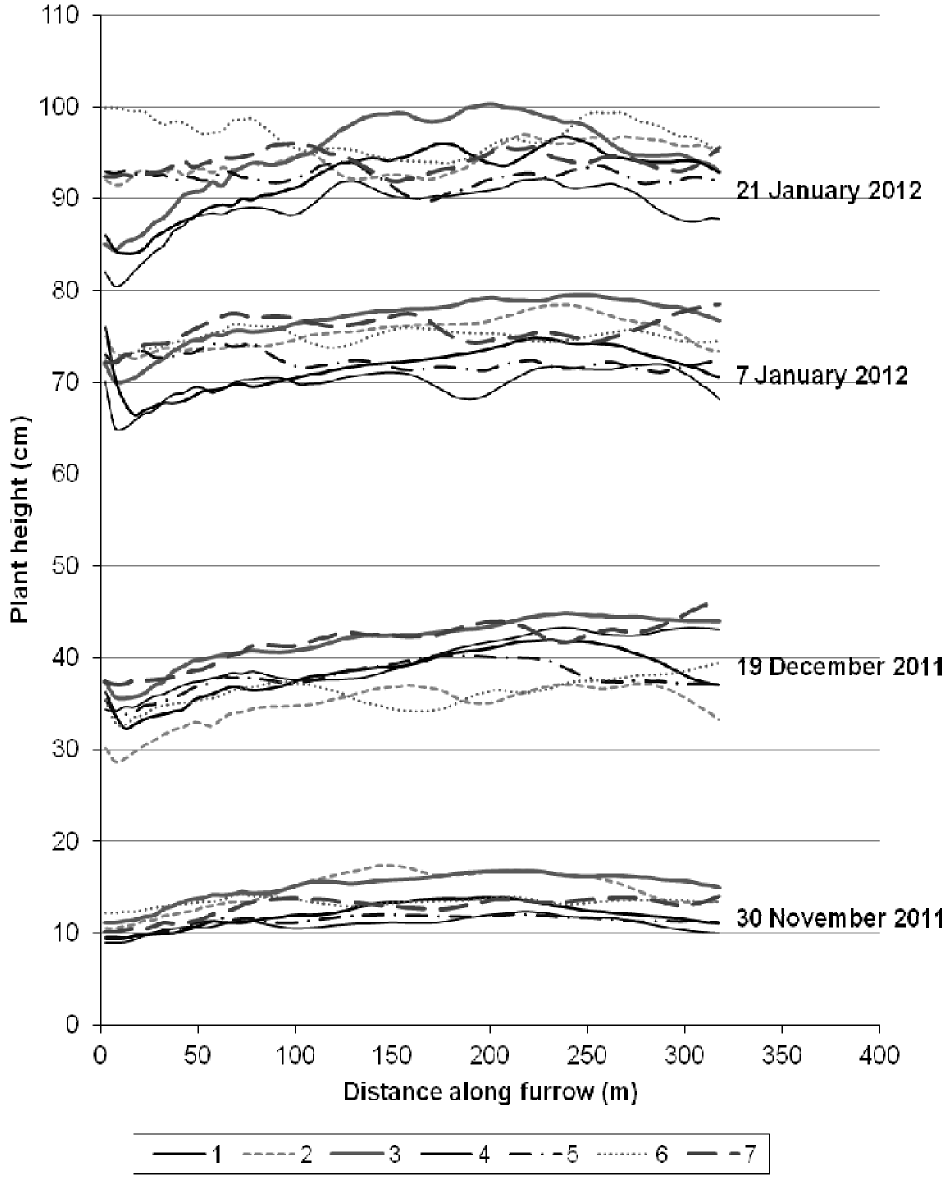


Figure 7.6: Plant sensing system estimated cotton plant height along seven furrows in trial

Flower count

The image analysis described in Section 2 was implemented on images collected using the ground-based plant sensing system to estimate the flower count on 7 January 2012 and 21 January 2012 (Figure 7.7). These measurements were used to estimate the square count as detailed in Section 7.2.6. The number of flowers was lower on 20 January 2012 than on 7 January 2012 as bolls formed. On 7 January 2012 there were more flowers at the head ditch, whilst on 20 January 2012 there was improved uniformity in the flowers along all the furrows.

The lowest flower counts were measured in the uncontrolled furrow (furrow 1) and in the furrows under the MPC strategy that aimed to fill the soil-water profile (furrows 2 and 5). These furrows also produced shorter plants, indicating that the irrigation application was not optimising yield.

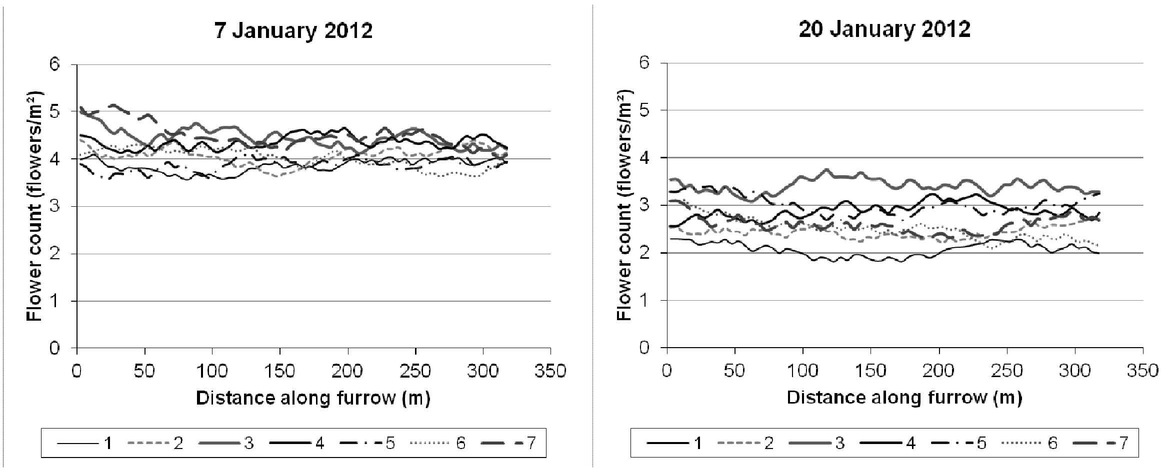


Figure 7.7: Plant sensing system estimated flower count along seven furrows in trial

Boll count

Boll counts were estimated using the plant sensing system on 7 January 2012 and 21 January 2012 (Figure 7.8). Boll counts were generally highest at the head ditch which is consistent with the squares counts. On 7 January 2012 the boll count was lowest for the uncontrolled furrow (furrow 1) and the MPC strategy maximising yield (furrows 3 and 6), and highest for the MPC strategy maximising CWUI (furrows 4 and 7). On 20 January 2012 the boll count was lowest for the uncontrolled furrow (furrow 1) and the MPC strategy filling the soil-water profile (furrow 2 and 5). The lower flower counts in furrows 1, 2 and 5 followed on to lower boll counts in the same furrows, while boll development increased under the MPC strategy maximising yield (furrows 3 and 6).

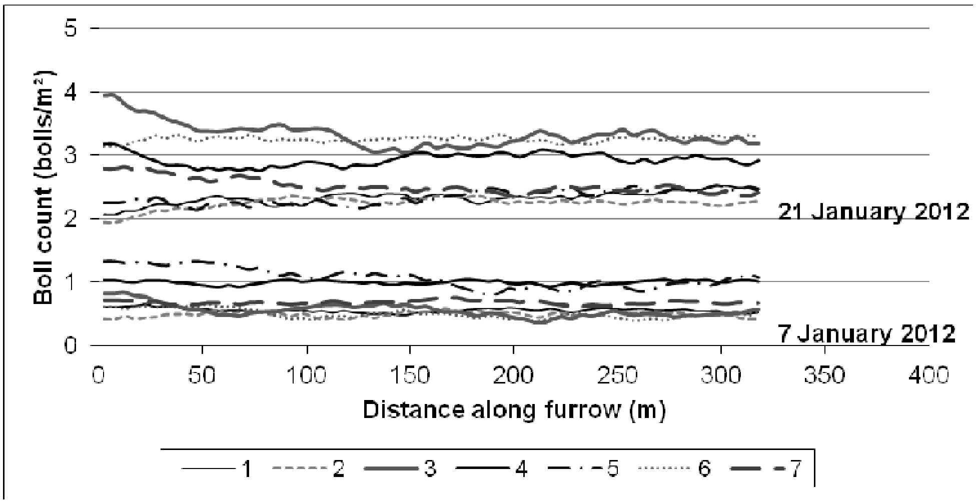


Figure 7.8: Plant sensing system estimated boll count along seven furrows in trial

7.4 IRRIGATION TREATMENTS

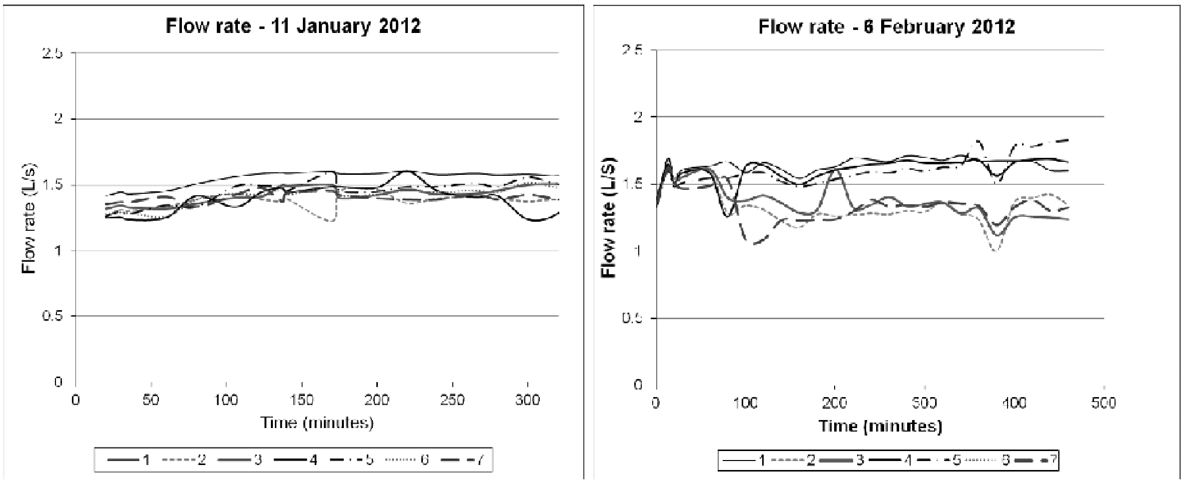
7.4.1 Optimal irrigation distributions based on Model Predictive Control

Optimal irrigation depths determined using VARIwise control strategies were compared with surface irrigation distributions estimated by the hydraulic model. The flow rate and advance trajectory corresponding to the closest hydraulic model distribution was implemented in the field.

The measured inflow rates are shown in Figure 7.9. Temporal variations in flow rate were caused by fluctuations in the head of the irrigation channel and changes in flow rate implemented according to the measured advance rate. There were larger variations in flow rate during the second controlled irrigation event than the first controlled irrigation event.

The flow rate in the uncontrolled furrow (furrow 1) was the most uniform of the furrows throughout both irrigation events (Figure 7.9). The flow rate in the uncontrolled furrow was 9.1% higher than the other furrows during the first irrigation event, and 9.3% higher than the other furrows during the second irrigation event.

During the second irrigation event the flow rate in furrows 2, 3 and 7 were approximately 30% lower than the other furrows (Figure 7.9(b)). The flow rate in these furrows was reduced to minimise the difference between the measured and optimal advance rate. This demonstrates a potential 30% reduction in water use using adaptive control of surface irrigation.



(a) (b)

Figure 7.9: Flow measurements during controlled irrigation events on: (a) 11 January 2012; and (b) 6 February 2012

Figures 7.10 and 7.11 compare the predicted, measured and fitted (to the measured) advance rates and irrigation depths along each furrow in the trial for the controlled irrigation events on 11 January 2012 and 6 February 2012, respectively. The advance rate for the uncontrolled furrow was generally faster than the controlled furrows. In the both irrigation events for the uncontrolled furrow the advance front reached the end of the field in under 500 minutes, and for the controlled furrows the advance front reached the end of the field in 550-600 minutes. This is because flow rate was generally higher for the uncontrolled furrow than the controlled furrows.

The measured and optimal advance curves generally followed the same trends for each furrow and irrigation event. During the first irrigation event, furrows 4, 5 and 6 showed the largest variation between measured and optimal advance rates (Figure 7.10). From Figure 7.9 the flow rate in these furrows was higher that the flow rate in other furrows during the subsequent irrigation event. This suggests that the infiltration parameters calculated for these three furrows before the first irrigation event may have been less accurate than those for the other furrows.

The infiltration parameters were updated after each irrigation event using the irrigation measurements (Table 7.3). The predicted flow rates were implemented at the start of each irrigation event, and the measured advance trajectory for each furrow was updated.

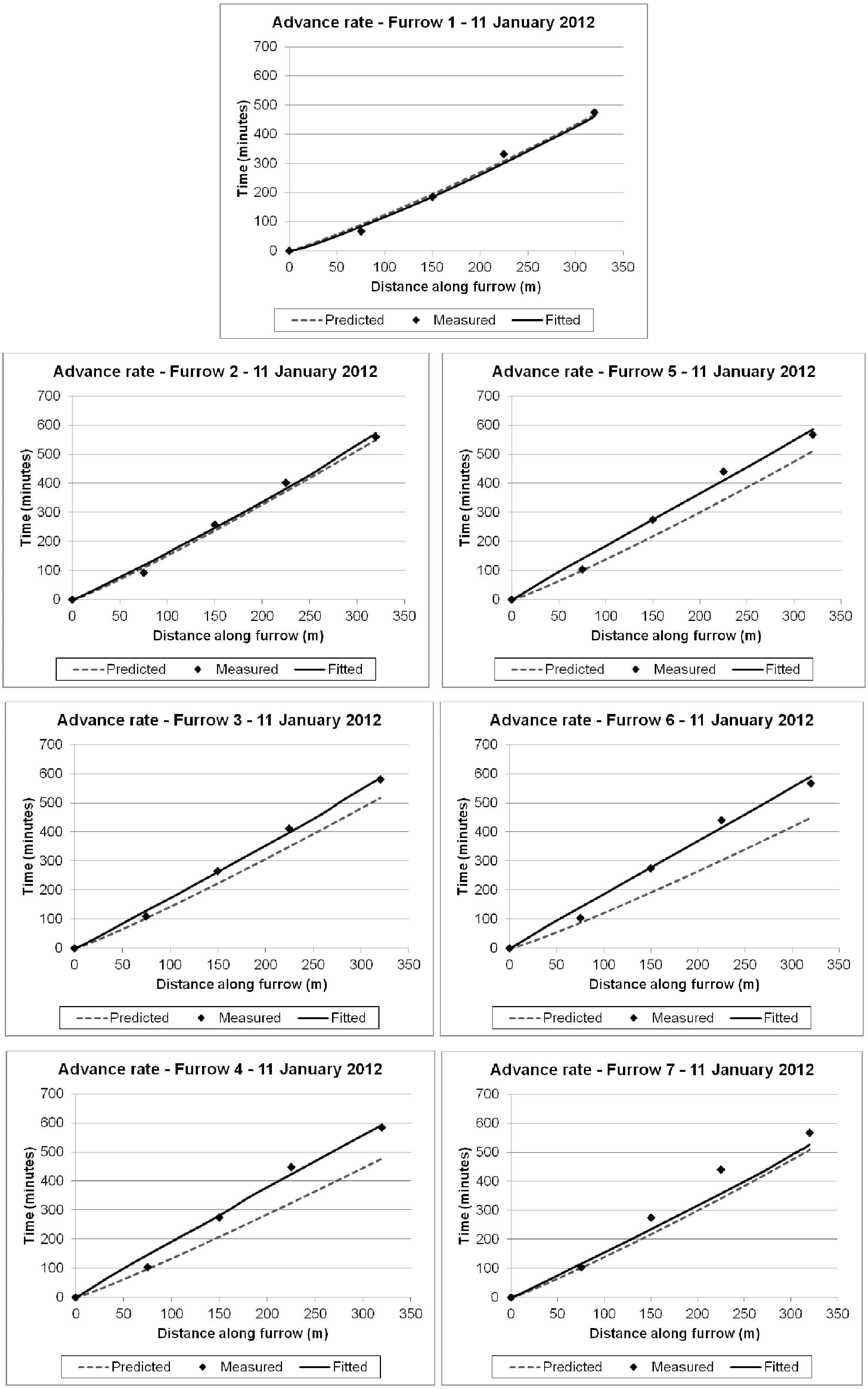


Figure 7.10: Comparison of measured and predicted advance rate on 11 January 2012 for controlled furrow

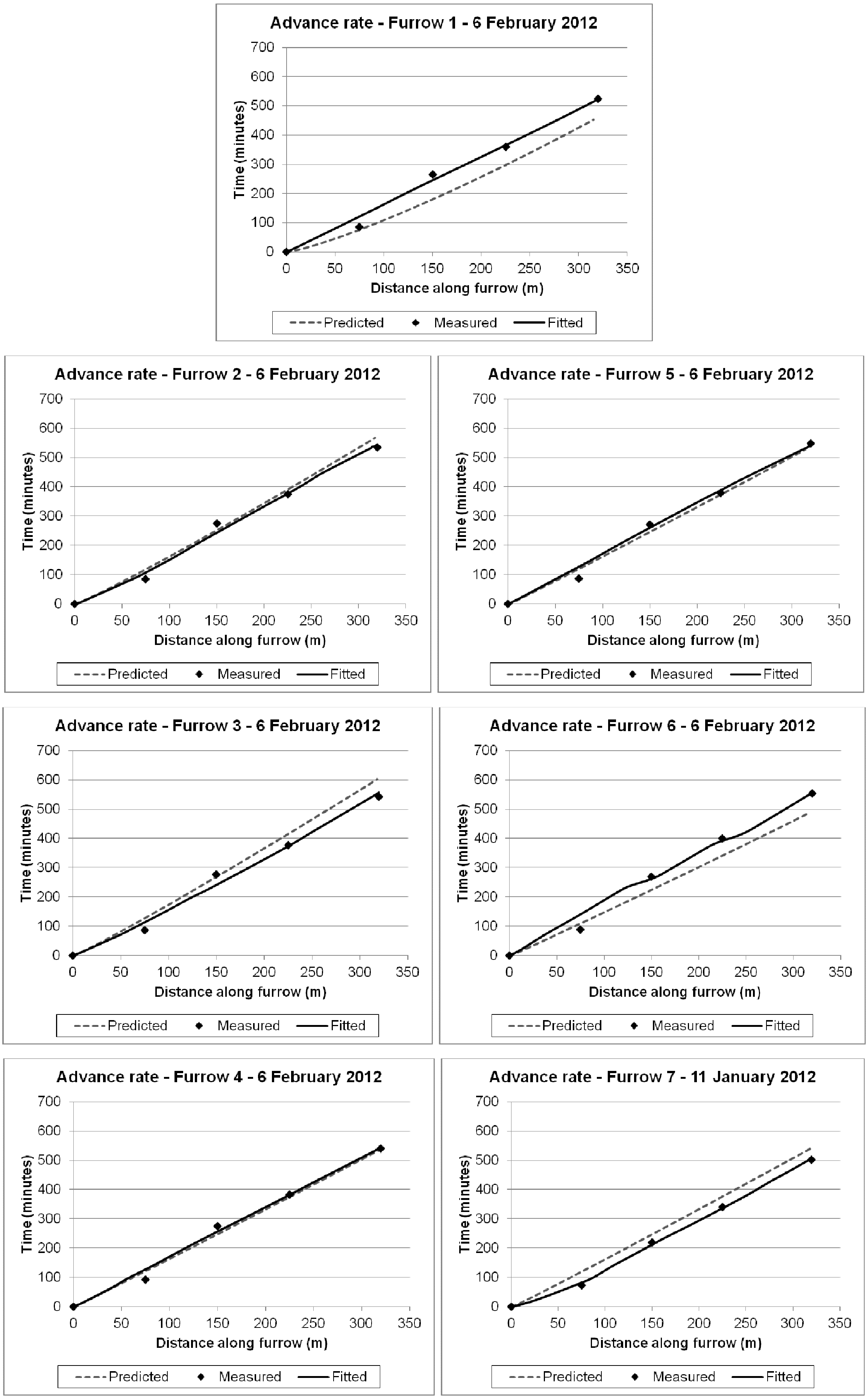


Figure 7.11: Comparison of measured and predicted advance rate on 6 February 2012 for controlled furrow

Table 7.3: Infiltration parameters for each irrigation event

Irrigation event	Furrow	a	k (m^3/min/m)	f_0 (m^3/min/m)	Predicted flow rate (L/s)
Monitored	1	0.0589565683777	0.0794507416362	0.0000656496551	N/A
	2	0.1030337398	0.0725864583	0.0	N/A
	3	0.0799598857140	0.0705296081201	0.0000088132909	N/A
	4	0.0912000045368	0.0725864583404	0.0	N/A
	5	0.0935643628830	0.0752141703366	0.0000184720707	N/A
	6	0.1177393446349	0.0592889365379	0.0	N/A
	7	0.0706102845648	0.0774184895738	0.0000288359741	N/A
Controlled irrigation 1 (600 minutes)	1	0.2126339238351	0.0395621168565	0.0	N/A (1.6)
	2	0.0815683173652	0.0851340481073	0.0	1.3
	3	0.0694214676407	0.0987294135582	0.0	1.4
	4	0.0072291236000	0.1407759106603	0.0000084791236	1.4
	5	0.0210766392075	0.1315179739276	0.0000045328742	1.5
	6	0.0090860970657	0.1352489923098	0.0000203794777	1.4
	7	0.0335106549150	0.1034843839558	0.0	1.4
Controlled irrigation 2 (550 minutes)	1	0.0057198932751	0.1349575520827	0.0000063448933	N/A (1.6)
	2	0.0163819368056	0.1153580729180	0.0	1.3
	3	0.0180560077201	0.1174032627466	0.0	1.4
	4	0.0124922359500	0.1379939441057	0.0000124881336	1.6
	5	0.0121670111997	0.1381918960503	0.0000182505168	1.6
	6	0.0182837972022	0.1466652883133	0.0000247630230	1.7
	7	0.1496826627986	0.0512551122378	0.0	1.3

Figures 7.12 and 7.13 show the optimal, predicted and fitted infiltration distribution along the furrows in the trial for the controlled irrigation events on 11 January 2012 and 6 February 2012, respectively. There was an average standard deviation in irrigation application along the furrows of 16.9 mm for the first controlled irrigation event and 9.6 mm for the second controlled irrigation event. This is consistent with the higher standard devaiations of soil-water along the furrows of 10.7 mm on 7 January 2012 and 12.1 mm on 21 January 2012 (Figure 7.4).

Across the different treatments there was a standard deviation in the optimal irrigation depths of 0.20 mm for the first irrigation event and 0.25 mm for the second irrigation event. There was no significant difference in the optimal irrigation distributions between the control strategies. The standard deviation of irrigation depths in each furrow was generally higher for the predicted irrigation distribution than the irrigation distribution fitted using the updated infiltration parameters.

The plants near the tail drain required less irrigation application which corresponds with the lower plant available water capacity in this area (Figure 7.12 and 7.13). The soil-water and plant available water capacity were also lower in the tail drain: this suggests that these plants consumed less water than those in the head ditch as they produced fewer flowers but were taller than the plants near the head ditch. Hence, it was likely these plants consumed water for vegetative growth rather than fruit development.

The optimal irrigation depths were generally highest at the start and middle of the furrows (Figures 7.12 and 7.13). This is generally consistent with the spatial trends of the soil-water and plant available water capacity graphs which were highest at the middle of the furrow (Figure 7.4).

The largest differences between predicted and fitted infiltration distributions occurred for furrows 4, 5 and 6 during the first irrigation event, and furrows 3 and 6 during the second irrigation event. This corresponds with the measured advance rates not following the optimal advance rates closely on the same furrows and irrigation event: this indicates potential inaccuracies in the infiltration parameters from the monitored irrigation event on 27 December 2011.

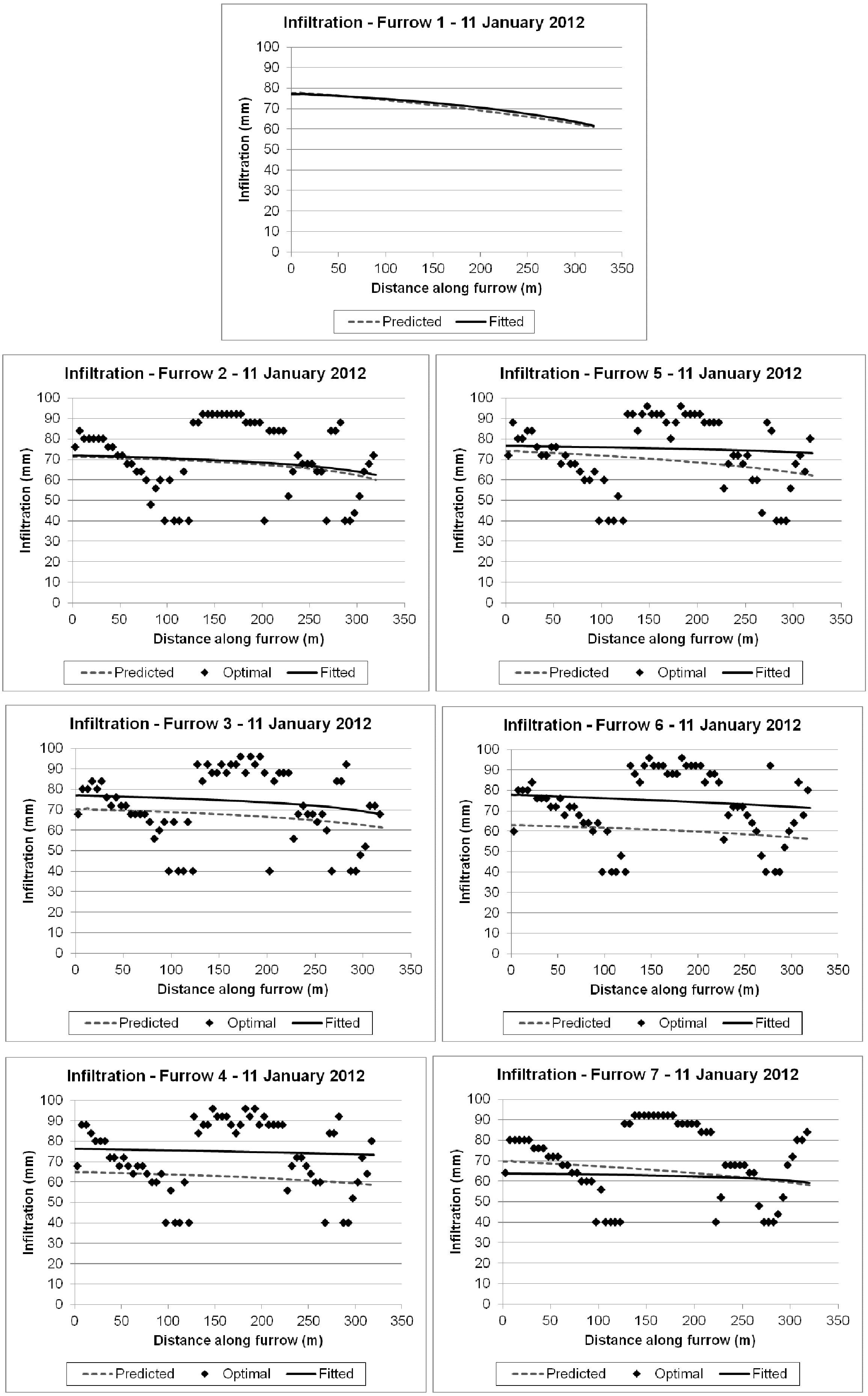


Figure 7.12: Comparison of irrigation application on 11 January 2012 according to: (i) model predictive control strategy; (ii) closest hydraulic model distribution; and (iii) fitted distribution

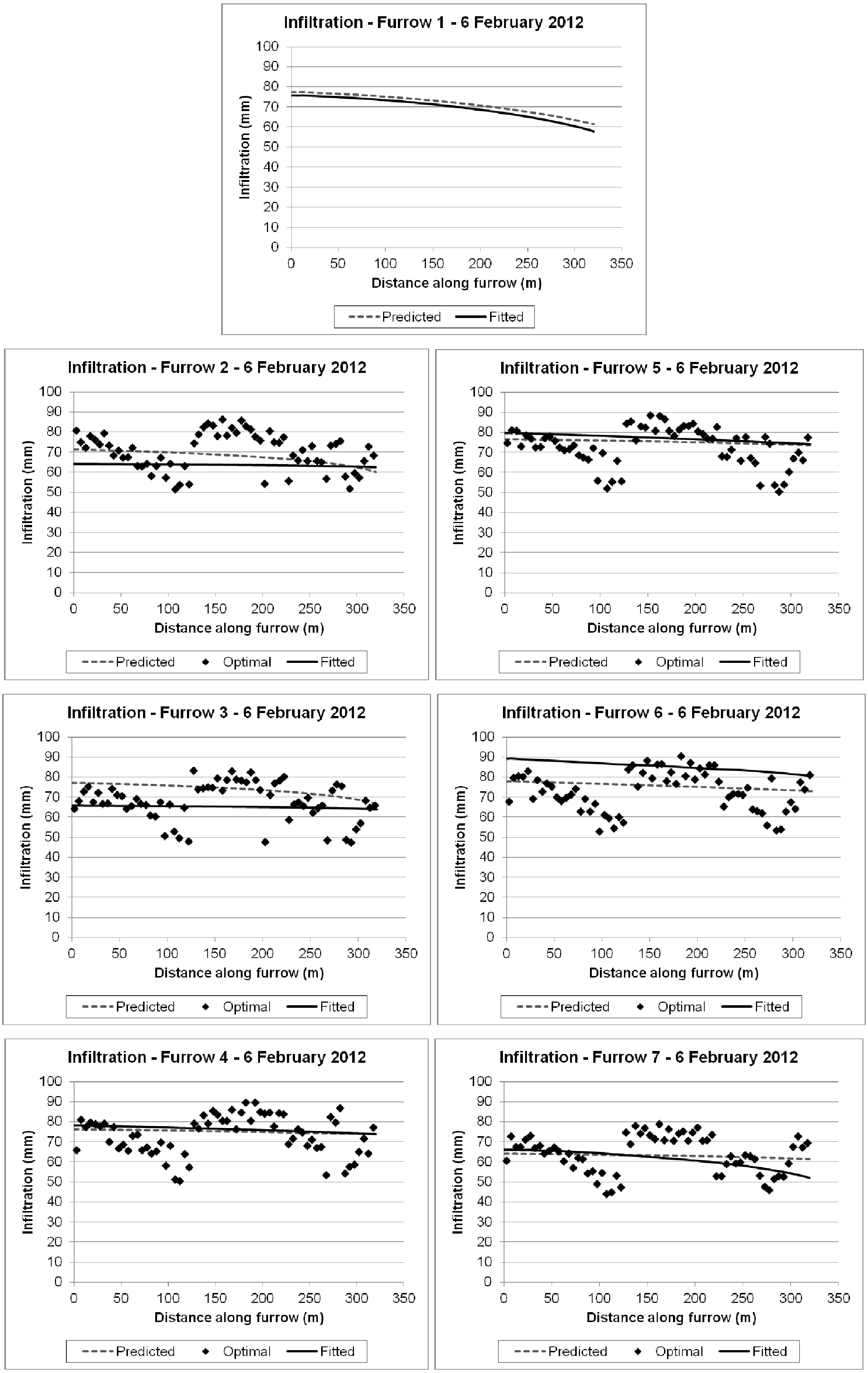


Figure 7.13: Comparison of irrigation application on 6 February 2012 according to: (i) model predictive control strategy; (ii) closest hydraulic model distribution; and (iii) fitted distribution

7.5 RESULTS AND DISCUSSION

7.5.1 Control strategy performance - irrigation

The irrigation performance results of the two controlled irrigations are shown in Table 7.4. The performance results in Table 7.4 include application efficiency which is the proportion of the volume of water added to the root zone to the volume of water applied to the field (Walker 1989). Irrigation system performance measures typically compare the irrigation volume applied to the volume required to fill the soil-water profile, and the uniformity of the irrigation application. As these performances are not desirable in this experiment, another performance measure 'irrigation requirement index' is defined in this paper as the proportion of volume of water added to the root zone to the optimal volume of irrigation application.

Table 7.4: Performance of evaluated irrigation control strategies

Irrigation treatment	Controlled irrigation 1		Controlled irrigation 2	
	Application efficiency	Irrigation requirement index	Application efficiency	Irrigation requirement index
Grower's irrigation treatment	85.9%	N/A	80.5%	N/A
Achieve full soil profile	87.2 ± 3.0%	96.6 ± 2.2%	91.9 ± 2.7 %	90.0 ± 0.1 %
Maximise yield	86.5 ± 1.3%	89.0 ± 3.5%	88.3 ± 1.8 %	86.0 ± 0.2 %
Maximise crop water use index	87.5 ± 3.4 %	96.1 ± 0.2%	88.4 ± 2.3 %	82.8 ± 0.2 %

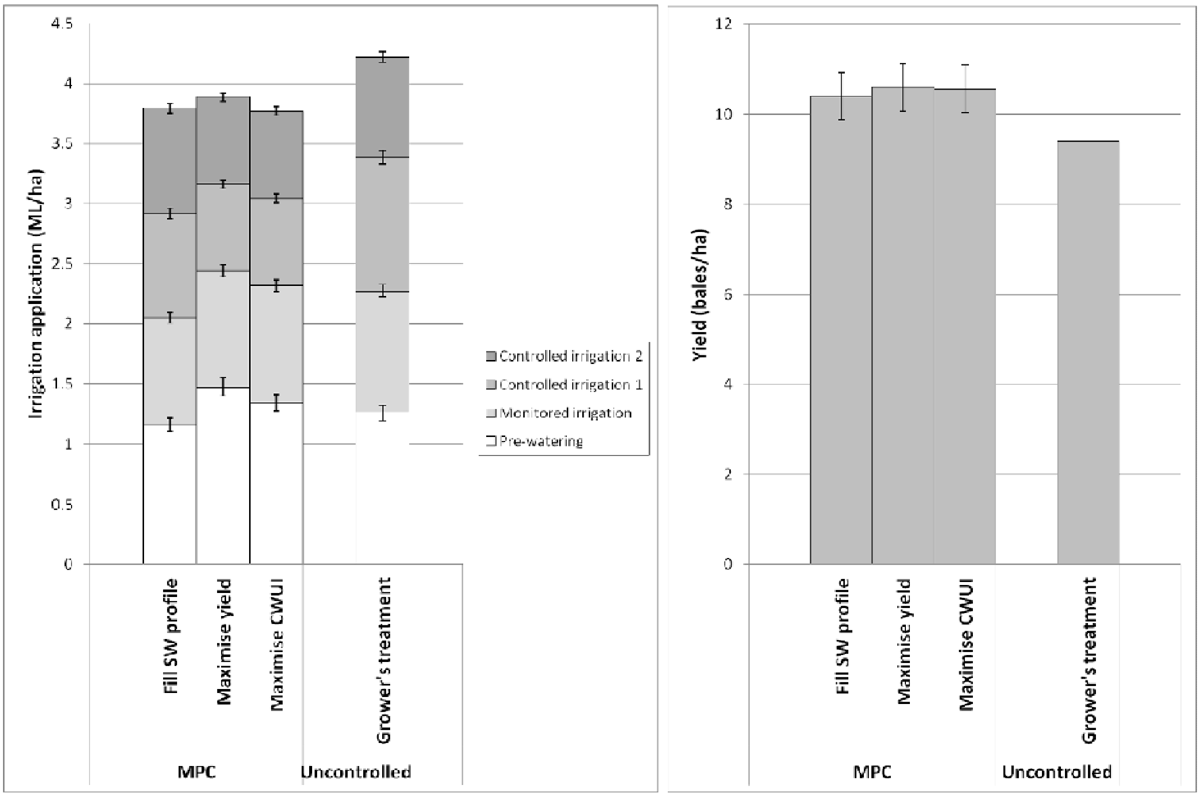
Controlling the irrigation events increased the application efficiency by an average 6%: this is because generally higher irrigation volumes were applied at the tail drain ends of the furrows and led to improved uniformity in irrigation application along the furrows.

The application efficiency and irrigation requirement index were generally lowest in the furrows that aimed to maximise yield. This is because this strategy did not consider the amount of water to determine the irrigation requirement which could have led to increased irrigation application.

The calculated irrigation requirement indices were 8.1% higher during the second irrigation event than the first irrigation event. This is because the irrigation treatments were more uniform along the furrows and the fitted curves were closer to the optimal curves during the second irrigation event than the first irrigation event.

7.5.2 Control strategy performance - yield

Figure 7.14 displays the control strategy water use and final yield where irrigation applied was measured using the ultrasonic flow meters and yield was estimated from hand sampling on 22 May 2012 before harvest on 23 May 2012. The involved taking manual cotton measurements from a representative 70 cm length of cotton plants near the start and end of each furrow in the trial.



(a) (b)

Figure 7.14: Results of evaluated irrigation control strategies: (a) irrigation application; and (b) final yield

This shows similar yields and final irrigation applications across the controlled furrows. However there was an average 12% water saving and 10% yield improvement. The water savings were achieved by reducing the flow rate to enable infiltration at the end of each furrow without extended the cut-off times of the irrigation events. The yield improvements were caused by the improved infiltration at the tail drain end of the field.

The yields and irrigation applications were similar for each controlled irrigation treatment (Figure 7.14) with the exception of the measured irrigation application during a pre-watering irrigation event in the furrows that maximised yield (Figure 7.14(a)). This is because the irrigation requirements along each furrow followed similar trends for each irrigation treatment; hence, the performance objective of control strategies did not produce significant spatial difference in irrigation volumes to apply along each furrow. A larger difference spatial variability in soil properties and plant growth may be required to cause change in productivity under different performance objectives. This also suggests that general irrigation control 'rules' could be developed for different soil types to determine the optimal irrigation distributions and corresponding advance rates and cut-off times.

7.5 CONCLUSIONS

The model-based control strategy Model Predictive Control was implemented on a surface irrigation system to compare different performance objectives and utilised soil-water and on-the-go soil electromagnetic and plant sensing systems. The flow rates were adjusted to target the advance rate that produced the control strategy-determined infiltration distribution. The different irrigation treatments produced similar spatial irrigation requirement distributions along the furrows. The small difference in irrigation requirements between the control treatments did not produce noticeable differences in the irrigation application or subsequent yields. However, there was a significant productivity improvement utilising the control strategies to adjust the flow rates into the furrows. This indicates that some level of control to achieve spatial irrigation requirement patterns can improve irrigation and crop performance.

Further investigation is required to establish the amount of spatial variability in the field is required to benefit further from site-specific surface irrigation. Hence, further work will entail field evaluation of control strategies at different spatial resolution of data collection and application control.

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8. Field evaluation of adaptive control for CPLM irrigation

8.1 INTRODUCTION

The development of the plant sensing system (Section 2) and investigation of irrigation control hardware (Section 6) has provided the sensors and hardware to enable the field evaluation of adaptive control strategies. Three adaptive control strategies 'Iterative Learning Control' (ILC), 'Iterative Hill Climbing Control' (IHCC) and 'Model Predictive Control' (MPC) have been developed and simulated in VARIwise.

A field evaluation was conducted to evaluate the performance of the strategies on a large mobile irrigation machine and compare these results with simulations. To conduct this evaluation a modest field experiment was designed and involved implementation of ILC and MPC control strategies. IHCC was not evaluated as it requires many test cells which is not feasible in the proposed fieldwork. This evaluation also enabled the identification of the data requirements of the MPC control strategy that provided sufficient calibration of the crop model. Minimising the data requirements would provide an irrigation monitoring and control system that would be more practical for implementation in commercial cotton production.

8.2 MATERIALS AND METHODS

Cotton variety Sicot 74BRF was sown under a 305 m long centre pivot irrigation machine on 9 October 2012 in Jondaryan, QLD. A vertical EM survey was conducted on 19 September 2012 to select the locations of the groups of replicate plots that were relatively uniform (Figure 8.1). Urea was broadcast on the cotton crop on 5 January 2013 and the soil nitrogen content was estimated to be 170 kg/ha by the farm's agronomist.

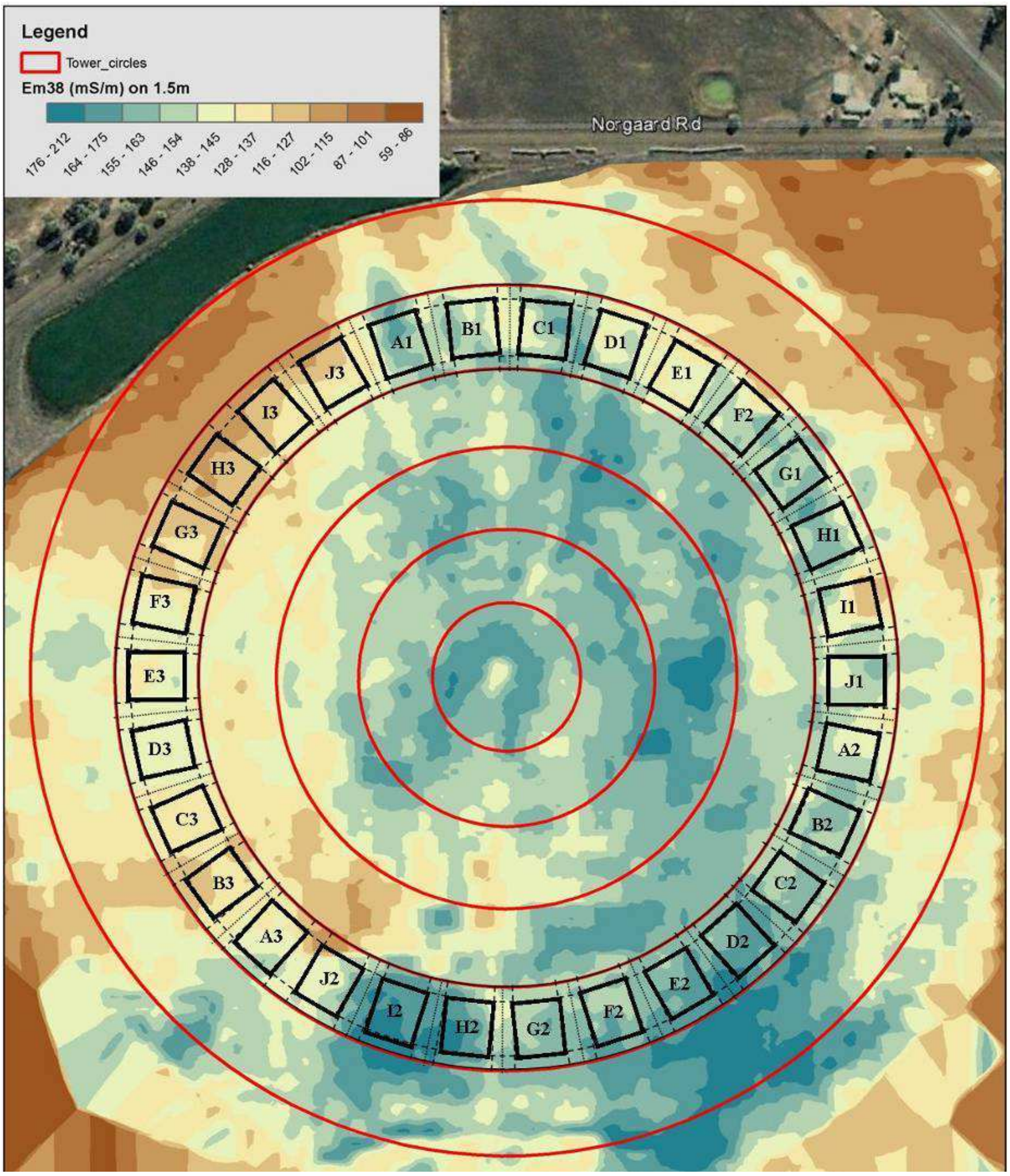


Figure 8.1: Horizontal EM survey conducted on Jondaryan field trial site

8.2.1 Irrigation treatments

The fieldwork evaluated three replicates of ten control strategies shown in Table 8.1. This compared the irrigation amounts applied and crop performance of MPC strategies utilising different combinations of performance objectives and data inputs, and ILC strategies which do not require a model to determine irrigation applications. Two plots of an industry-standard irrigation treatment using FAO-56 were also implemented for comparison with the control strategies. The deficit ILC and FAO-56 strategies targeted a soil-water deficit of 90% of the plant available water capacity.

Table 8.1: Control strategies evaluated in 2012/13 fieldwork were W indicates weather data input, S indicates soil data input and P indicates plant data input

ID	Control strategy	Performance objective	Data input
A	MPC	Maximise yield	WSP
B	MPC	Maximise yield	WS
C	MPC	Maximise yield	WP
D	MPC	Maximise CWUI	WSP
E	MPC	Maximise CWUI	WS
F	MPC	Maximise CWUI	WP
G	ILC	Fill soil-water profile	WS
H	ILC	Achieve set soil-water deficit	WS
I	FAO-56	Fill soil-water profile	WS
J	FAO-56	Achieve set soil-water deficit	WS

One span of the centre pivot irrigation machine 48 m long was selected to be controlled for the trial. This span contained fifteen sprinklers with a throw of 16 m (Nelson Spinner with 3TN nozzles). An 8 m buffer was allowed across the span such that each plot was 32 m wide and 27 m long. The irrigation application was varied midway between the plots as the machine passes over the field.

The nozzles on this span were changed to increase the maximum flow rate that could be achieved and enable higher irrigation volumes to be applied if required by the control strategy. The nozzle size on the controlled span increased from an average of 28 to 32, which increased the flow rate 22% at a pressure of 25 psi.

A ball valve and flow meter (GSD5 Single-Jet 13 mm cold water meter with one pulse output per litre) were installed on each dropper. The irrigation valves and flow meters were connected to an ‘irrigation controller’ computer also installed on the irrigation machine tower. A GPS with an accuracy of 0.5 m was located in the centre of the span.

A remote computer running VARIwise collated the weather station, soil-water and real-time plant sensor data to determine the required irrigation depth. This remote computer then updated a file on a remote server containing the percent of irrigation applications required for each sprinkler. The irrigation controller computer checked this file and adjusted the valves accordingly.

8.2.2 Field measurements

An Environdata Weathermaster 2000 automatic weather station was located next to the field with the trial. Rain gauges were installed and manually monitored at four locations in the corners of the field to measure the spatial variability of rainfall.

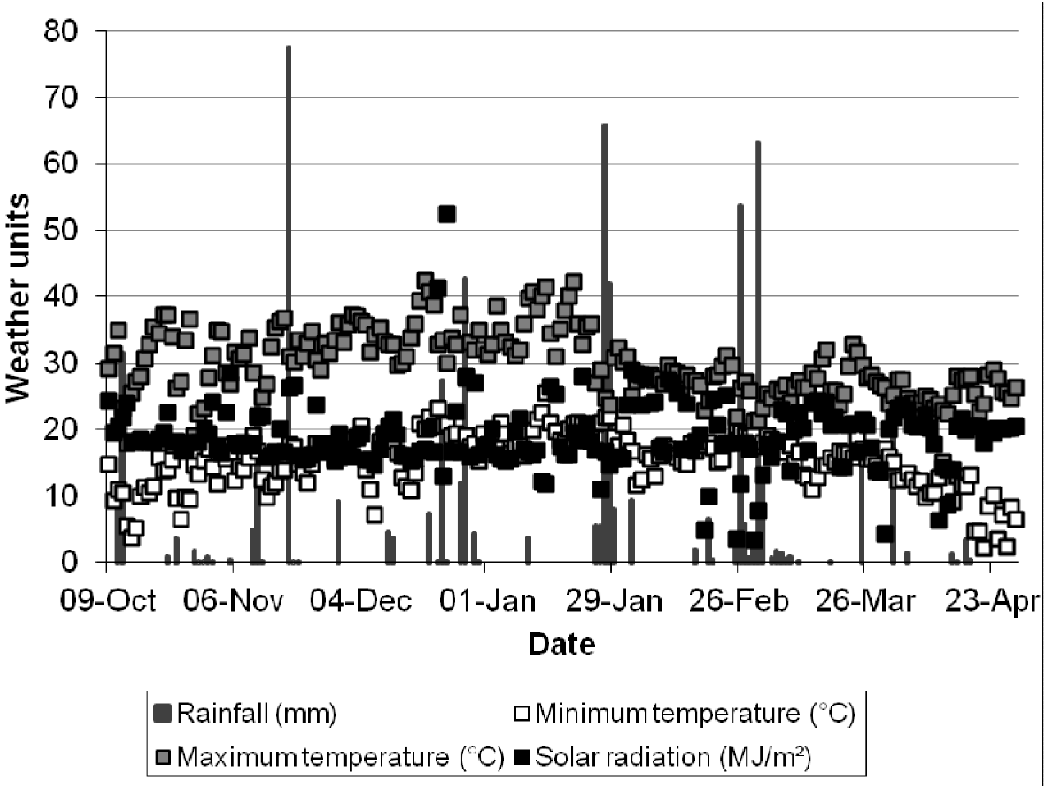


Figure 8.2: Weather data during centre pivot irrigation trial in Jondaryan, Queensland

Soil measurements

Groups of three soil-water sensors (MP406 standing wave sensors, ICT International) were installed in seven of the plots onto a web server (Silicon Chip, Webserver in a Box) on 8 November 2012 after the cotton had germinated. A DUALEM sensor was used to collect soil EM maps throughout the crop season to estimate the change in soil-water over the whole field. The EM measurements were then used to estimate plant available water capacity and soil-water to calibrate the crop model following the procedure of the surface irrigation trial (section 7.2).

Plant measurements

Four plant sensing systems were developed and mounted on the centre pivot irrigation machine, three evenly across the controlled span and one on the span next to the trial for comparison with the field trial. These sensing systems were used to estimate plant density from images at the start of the season, plant height to estimate leaf area index, flower counts to estimate number of squares, and boll counts (described earlier in Section 2). An on-ground, vehicle-based plant sensing system that estimated these plant parameters was also evaluated on 10 October 2012, 15 November 2012, 25 December 2012, 3 January 2013 and 17 January 2013. The DUALEM sensor was connected to the vehicle-based plant sensing system on these measurement days and the EM readings were recorded with the plant images and measurements.

8.3 FIELD DATA AND PROCESSING

8.3.1 Soil-water

Soil-water was measured in plots B1 (sensor 1), A1 (sensor 2), J3 (sensor 3), I3 (sensor 4), H3 (sensor 5), E3 (sensor 6) and D3 (sensor 7) defined in Figure 8.1 between November 2012 and March 2013 (Figure 8.5). The change in soil-water during rainfall events before the first irrigation event on 19 December 2012 was used to calibrate the soil-water sensors. This was achieved using the rainfall events of 24 mm on 11 November 2012, 78 mm on 18 November 2012 and 9 mm on 29 November 2012. The soil-water readings were further adjusted according to the plant available water capacity of the grey clay loam soil in the field which was determined from soil samples taken in August 2012 to be 145 mm (Figure 8.3).

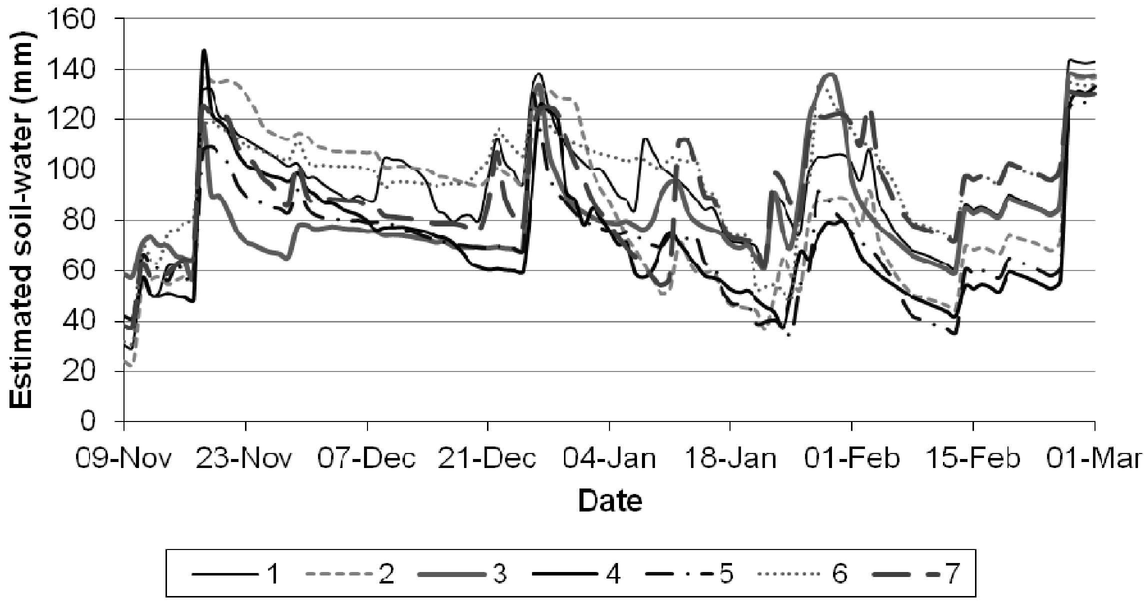


Figure 8.3: Volumetric soil-water measured daily in seven plots of the field trial

The EM measurements taken throughout the cotton season were used to determine correlations between soil-water and EM. Linear regression equations were established between averaged EM measurements within five metres of the centre of each plot and soil-water readings in each measured plot (Table 8.2). These equations were used to estimate the plant available water capacity and soil-water in each plot of the trial (Figures 8.4 and 8.5).

Table 8.2: Estimation of the plant available water capacity and soil-water using EM measurements where *y* is the soil-water and *x* is the EM

Date	Measurement	Regression	Goodness of fit
11, 18, 29 November 2012	Change in soil-water	$y = 6.5123x + 4.6656$	0.7940
15 November 2012	Plant available water capacity	$y = 0.7152x – 0.0160$	0.4687
15 November 2012	Soil-water	$y = 0.4559x + 33.857$	0.6025
25 December 2012	Soil-water	$y = 0.5644x – 5.570$	0.5708
3 January 2013	Soil-water	$y = 0.3260x + 24.417$	0.8641
17 January 2012	Soil-water	$y = 0.3060x + 34.971$	0.6075

The measured plant available water capacity was lowest in replicate three of the trial (which is consistent with EM map in Figure 8.1). It follows that the soil-water was lowest in replicate three. The measured soil-water was generally lowest under the FAO-56 control strategies (treatment I and J) and highest under MPC maximising CWUI without soil-data (treatment F) and the ILC strategy that filled the soil-water profile (treatment G).

8.3.2 Plant measurements

Figures 8.4 and 8.5 display the plant measurements taken throughout the cotton season at the centre of each trial plot. There were spatial variations in plant density around the field with a standard deviation of ± 2.9 plants/m² in the plots. It is likely that the primary contributor to this was uneven sowing density. The plant density was lowest in replicate three of the trial (with the lowest plant available water capacity). This indicates that the lower available water may have reduced soil-water and contributed to lowering the germinate rates. The highest plant densities were measured in the MPC plots that maximised CWUI (treatments E and F) and the ILC plots that filled the soil-water profile (treatment G). These treatment plots also had the highest irrigation application which may have contributed to the increased plant density.

The plant height was highest in the areas with higher plant densities (treatments E, F and G): this indicates that there were more favourable growing conditions in these areas. The plots where FAO-56 strategies were implemented (treatments I and J) produced the shortest plants. This is suggests that feedback in the irrigation control decision improved growing conditions. These results were consistent between the three trial replicates.

The MPC strategies that maximised yield (treatment A) and CWUI (treatment D) using all data input produced the highest square counts. The FAO-56 strategy that filled the soil-water profile (treatment I) also produced the highest number of squares. The lowest squares counts were detected in the MPC plot that maximised yield without using the plant data. Hence, the inclusion of plant data lead to improved model calibration and control strategy performance.

The plots in the second replicate generally produced the highest boll counts (corresponding with the soil with the highest plant available water capacity). The MPC strategies maximising yield with weather-and-plant input (treatment B) and maximising CWUI with weather-plant-and-soil input (treatment D) and the FAO-56 strategy that filled the soil-water profile (treatment I) produced the highest boll counts. This is consistent with the square counts. It should also be noted that plots with higher square and boll counts had lower plant densities and were shorter. This indicates that the cotton plants produced more bolls and produced fruit rather than vegetation when there was less competition for light and soil-water.

The lowest number of bolls were measured under the MPC strategy maximising CWUI without plant data input (treatment E) and the FAO-56 strategy achieving a set soil-water deficit (treatment J). This suggests that plant data is preferable to soil data for model calibration in adaptive irrigation control.

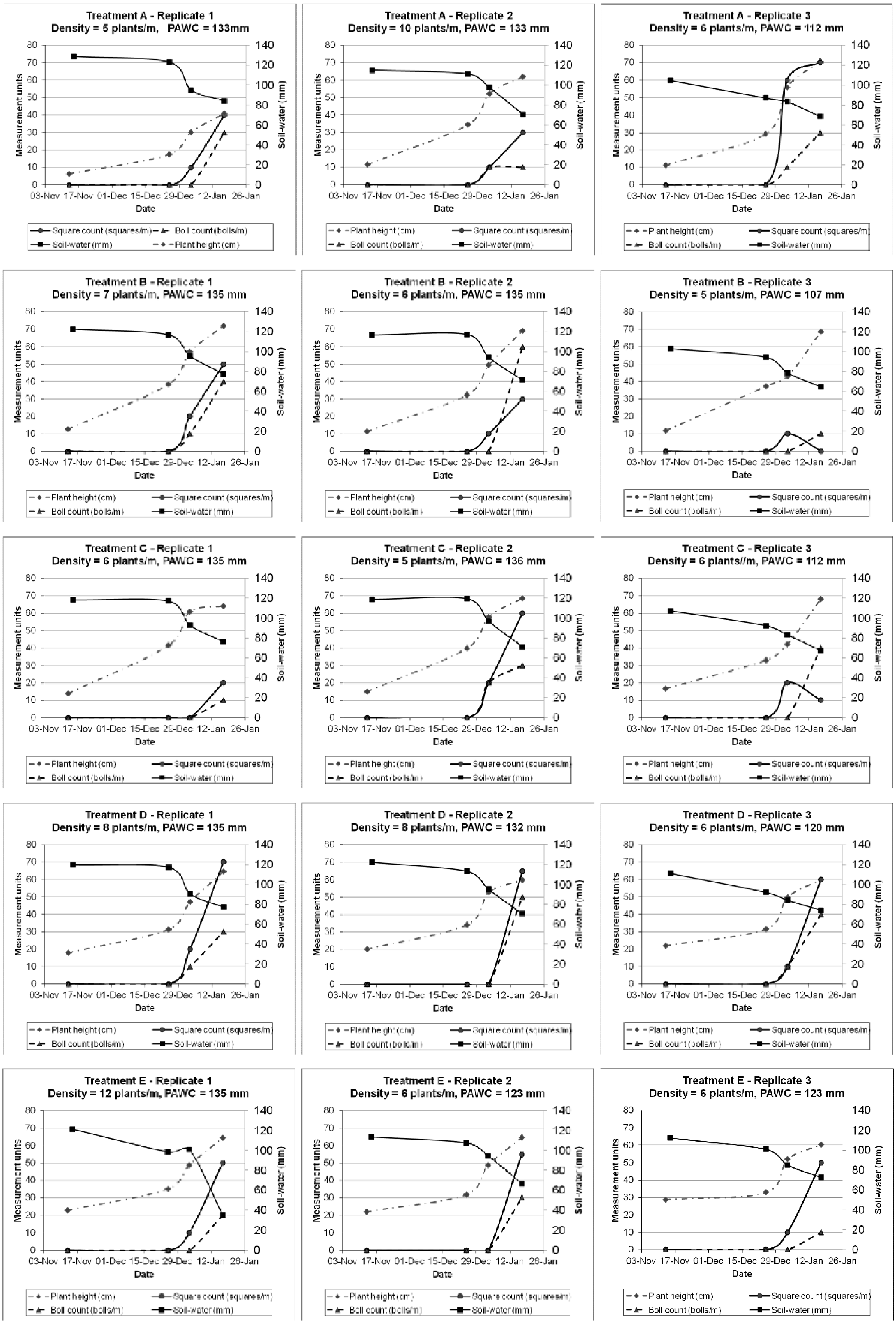


Figure 8.4: Estimated soil-water and plant parameters for treatments A-E

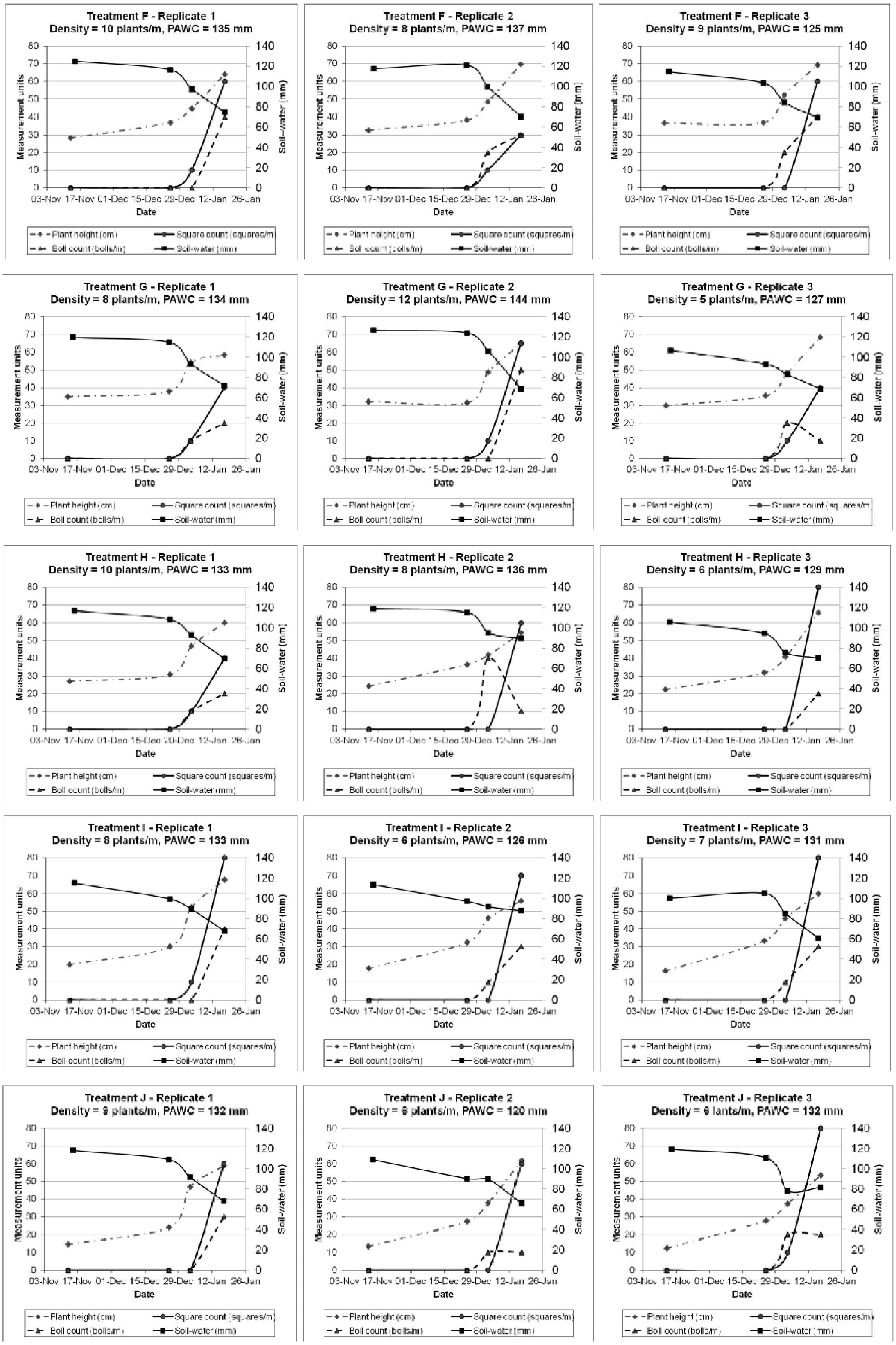


Figure 8.5: Estimated soil-water and plant parameters for treatments F-J

8.4 RESULTS AND DISCUSSION

The irrigation application was controlled during eight irrigation events on 19 December 2012, 21 December 2012, 5 January 2013, 7 January 2013, 18 January 2013, 22 January 2013, 26 January 2013 and 14 February 2013. The irrigation volumes applied and yield in each controlled plot are displayed in Figure 8.6.

8.4.1 Control strategy performance - irrigation

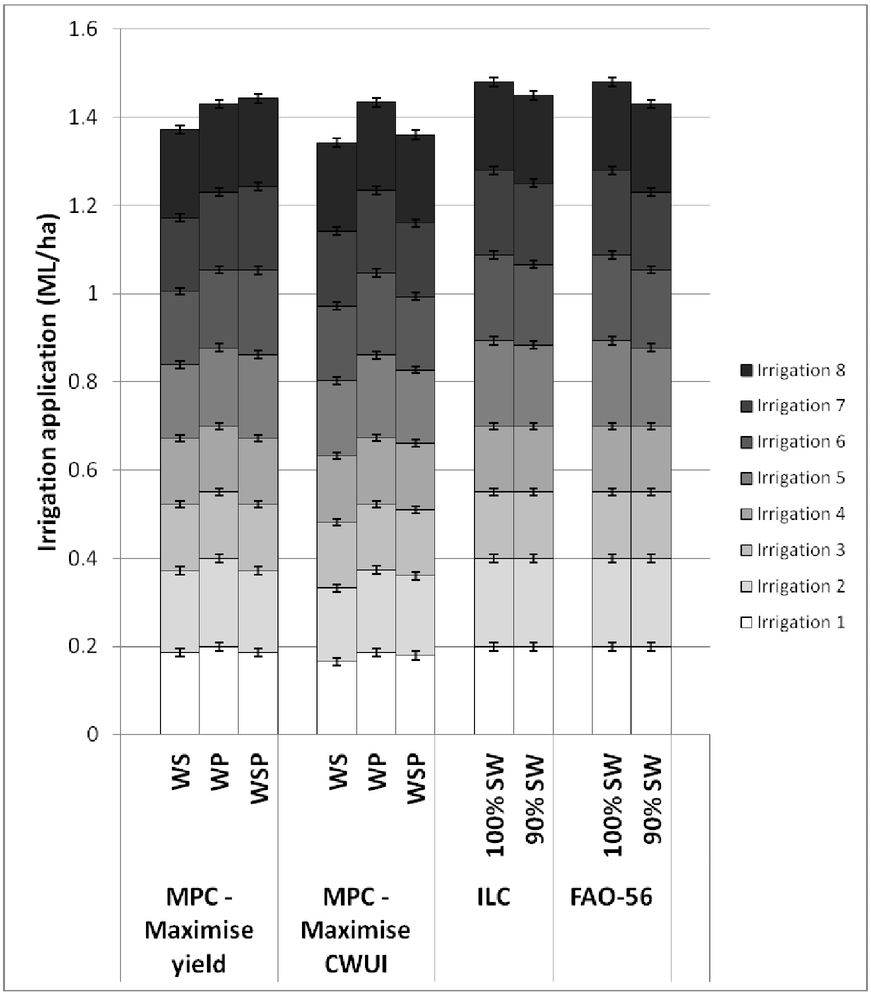
The lowest irrigation volumes were applied in replicate two of the trial (with the soil with the highest plant available water capacity). The highest irrigation volumes were applied using FAO-56 (treatments I and J) and ILC that filled the soil-water profile (treatment G). This is because the FAO-56 strategies did not use feedback to update the irrigation application and the ILC strategy was targeting a full soil-water profile.

The lowest irrigation volumes were applied using MPC that maximised CWUI with weather-and-soil input (treatment E) and weather-soil-and-plant input (treatment D) and MPC that maximised yield with weather-and-soil input (treatment B). This indicates that suboptimal irrigation applications may have been applied in treatment E and B as plant data input was not used by the irrigation control strategy. However, the strategy that maximised CWUI utilising all data input potentially was able to minimise the irrigation application to the crop.

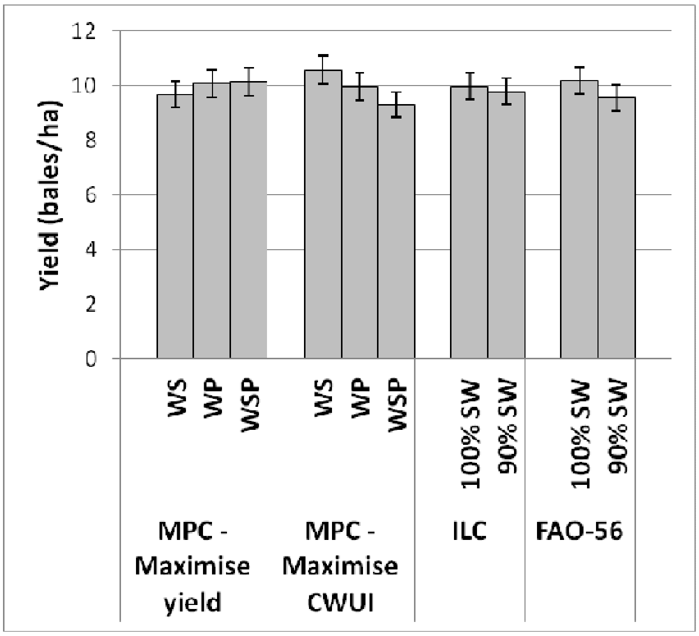
The ILC and FAO-56 strategies applied higher irrigation volumes than the MPC strategies. When targeting a 10% soil-water deficit, the ILC and FAO-56 strategies applied higher irrigation volumes and resulted in similar or higher yields than targeting a full soil-water profile. This indicates that the crop performance improved under a deficit irrigation strategy.

ILC consumed less water than FAO-56 treatment plots. This is because FAO-56 only applied the calculated crop water consumption, whilst ILC determined irrigation by comparing the desired and measured soil-water to account for any unpredicted differences in soil-water.

For both MPC strategies, the weather-and-soil input combination applied the lowest irrigation volumes. This indicates that the plant measurements increase the irrigation requirement calculated.



(a)



(b)

Figure 8.6: Results of field evaluation of adaptive control strategies on centre pivot irrigation machine: (a) irrigation volumes applied during each irrigation event averaged over the three replicates of each strategy; and (b) measured yield in each plot

8.4.2 Control strategy performance - yield

The yield in each plot was estimated from hand samples taken at the centre of each plot, the area of field covered by the sampled cotton and the measured seed turnout in each sample. The yield was lowest in replicate one where the soil had the lowest plant available water capacity. The lowest yields were also produced in the FAO-56 plots that targeted a soil-water deficit (treatment J) and MPC plots that maximised yield using weather-and-soil input and maximised CWUI using all input data.

The highest yields were produced in the plots that implemented the MPC strategies to maximise yield using all data inputs (treatment A) and maximise CWUI using weather-and-soil input (treatment E), and the FAO-56 strategy that filled the soil-water profile (treatment I). This generally corresponds with the plots that produced the highest square and boll counts (e.g. treatments A and I).

The MPC strategies that maximised yield produced higher yields as the level of data complexity increased, and the MPC strategies that maximised CWUI produced lower yields as the level of data complexity increased. In addition the MPC strategy that maximised yield produced the highest yield with full data input and lowest yield with weather-and-soil data input. This indicates that including plant input increases the accuracy of the yield prediction. These results are consistent with the performance objective of the MPC strategies implemented: the model calibration improved with more data inputs which led to high yields for MPC maximising yield, but reduced water use (and led to yield reductions) for MPC maximising CWUI.

ILC applied more irrigation than the MPC strategies with any data input, and generally achieved lower yields. As ILC required only soil data input, the ILC strategy would be suited for achieving higher yields with low data availability. However, under limited water the MPC strategies would be preferable.

Adaptive control yielded approximately 7% more cotton and applied 4% less irrigation water than FAO-56. The cotton under the adaptive control trial was also compared with cotton under the outer span of the irrigation machine which used the grower's irrigation treatment and with nozzles that applied 22% less water (Figure 8.7). The controlled span applied an average 11.85 ML/ha (0.84 bales/$ML_{irrigated}$), whilst the uncontrolled span applied 9.6 ML/ha (0.85 bales/$ML_{irrigated}$) (a 23% difference). There was an average 11% higher yield across the controlled plots than the uncontrolled span. This demonstrates that some level of irrigation control (utilising the FAO-56 strategy) can lead to significant water productivity improvements. HVI classification of the samples showed no significant different in lint quality between the two spans.

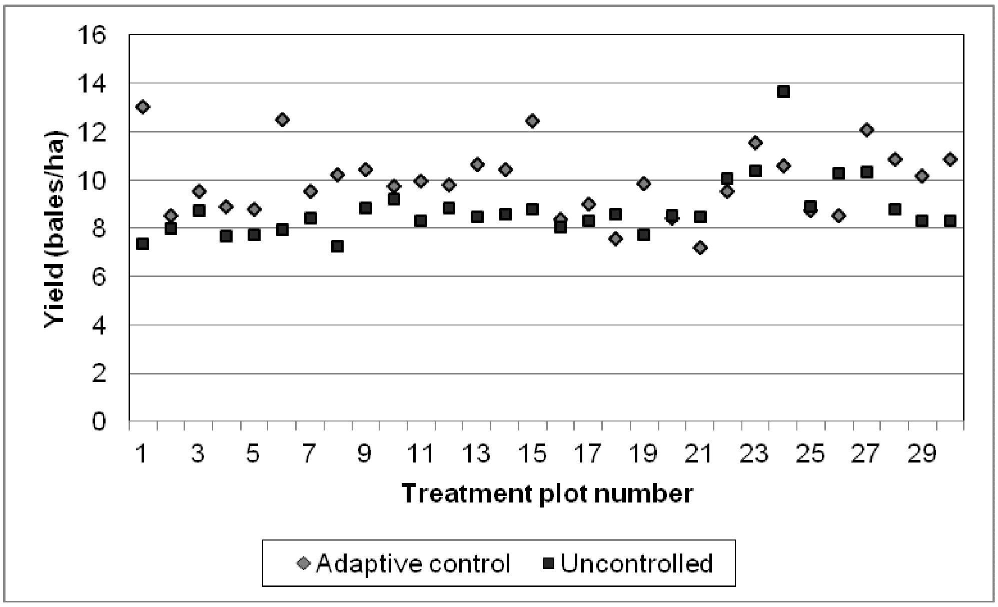


Figure 8.7: Comparison of yield in plots and in span next to plot

The adaptive control of irrigation produced lower water savings and yield improvements for the centre pivot trial than the surface irrigation trial. This indicates that is greater potential for water productivity improvements under surface irrigation systems than centre pivots and lateral moves. This is because larger irrigation volumes are generally applied in surface irrigation systems than in centre pivot and lateral move irrigation systems which can lead to less efficient management practices.

A yield map of the field was collected on 28 April 2013 (Figure 8.8). This shows an area of low yield through the middle of the yield which was likely caused by weeds in the field. The controlled (second-to-last outer) span has extended areas of darker green than the corresponding location on the uncontrolled (outer) span. The yields in the weed patch were similar under both spans.

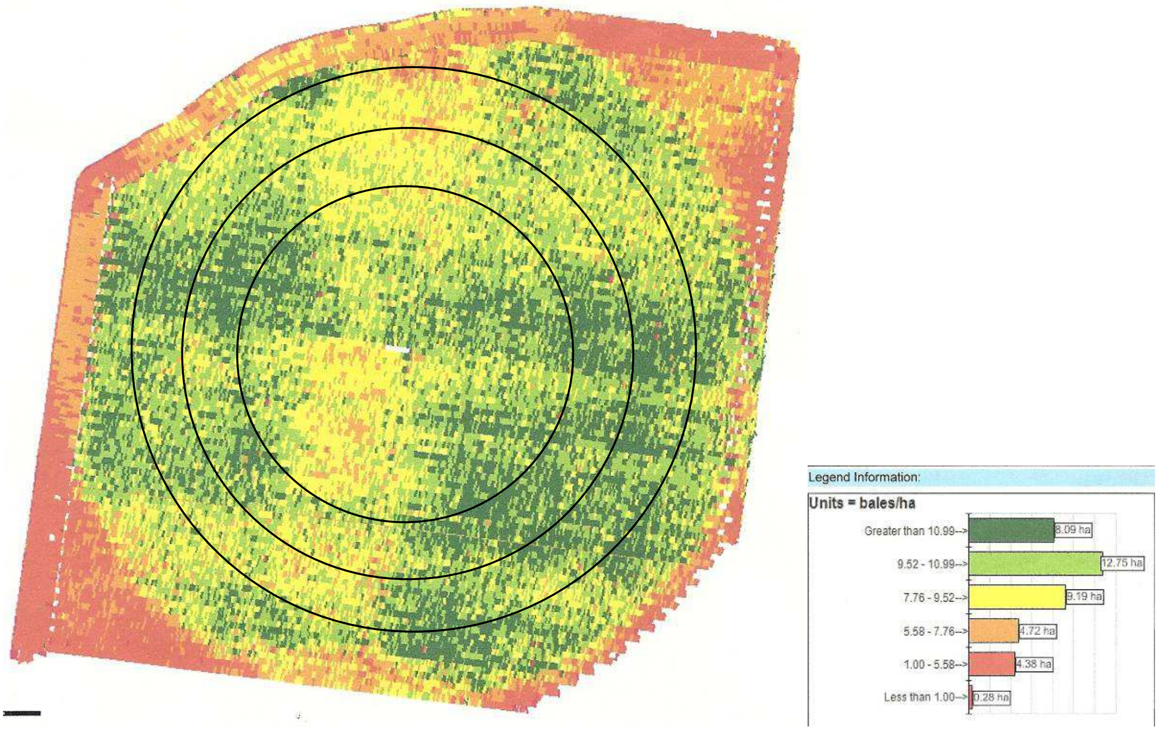


Figure 8.8: Yield map of centre pivot irrigated field where black circles indicate locations of towers on outer two spans of irrigation machine

8.5 CONCLUSION

A field evaluation of the Model Predictive Control and Iterative Learning Control strategies was conducted on one span of a centre pivot irrigation machine. This was used to evaluate the irrigation machine-mounted plant sensing system and comparison of control strategies with different data inputs. Plant data input generally increased the irrigation requirement calculated, but produced crop that aligned closer with the performance objective. This indicates that plant data would be preferable to soil data input in model-based adaptive irrigation control strategy implementations.

Irrigation control strategies (not necessarily adaptive) produced higher yield with reduced water applications compared with the grower’s treatment. The adaptive control strategies produced further yield improvements and water application reductions compared with the implemented FAO-56 strategy.

9. Conclusions and recommendations

9.1 ACHIEVEMENT OF PROJECT OBJECTIVES

This project investigated real-time irrigation control strategies and sensing systems required for automated irrigation control under commercial cropping conditions. The project demonstrated a closed-loop control system utilising infield sensors, site-specific decision making irrigation strategies and irrigation control hardware on surface and overhead irrigation systems.

A plant sensing system was developed to estimate leaf area index, square count, boll count and plant density. This system could be utilised for trials on either surface and centre pivot or lateral move irrigation systems. The sensing system was evaluated on a ground-based platform at a siphon irrigated site in 2010/11 and 2011/12 and mounted on a centre pivot irrigation machine in 2012/13. The overhead irrigation field evaluation indicated that plant data was preferable to soil data if only one data input was available. This suggests that the final irrigation control system may rely on plant data and not require a high spatial or temporal resolution of soil measurements.

Hydraulic modelling equations were utilised by VARIwise to convert the optimal irrigation depths calculated to an appropriate control action for surface irrigation systems (i.e. flow rate and cut-off time for surface irrigation). A methodology was developed that enabled spatially variable irrigation depths to be implemented by adjusting flow rate in siphon irrigation systems. Uncertainty in irrigation application caused by wind drift under sprinkler irrigation was also investigated. This indicated that the performance of the control strategies was not significantly affected under light wind.

Field evaluations of adaptive control strategies were conducted on a surface irrigation system (2011/12) and centre pivot irrigation system (2012/13). This enabled demonstration of the VARIwise control strategies integrated with: (i) data from infield weather station, soil-water sensors and plant sensing systems; and (b) infield flow rate and advance meters and control hardware. This combined approach demonstrated water savings of 4-12% and yield improvements of 7-11%.

The surface irrigation trial produced higher water productivity results than the centre pivot irrigation trial and indicates increased potential for water savings in surface irrigation using adaptive control. The control strategies with different performance objectives did not produce significantly different results in the surface irrigation trial.

9.2 EXTENSION OPPORTUNITIES

9.2.1 Commercialisation of VARIwise framework

The next step for the centre pivot and lateral move irrigation implementation is the commercialisation of the VARIwise framework. The NCEA intends to open dialogue with centre pivot and lateral move manufacturers with the view to get interest in the system leading to consideration for commercialisation opportunities.

9.2.2 Future dissemination of outcomes

A web-based guide that displays estimates of the irrigation and yield differences from a range of irrigation systems, climate scenarios and management strategies (e.g. site-specific vs uniform irrigation) would enable growers to evaluate potential impacts of irrigation control systems to specific farming systems. This guide (named 'VARIwise Lite) will enable the extension of the results to the industry and is being investigated as part of the CRDC-approved project 'Advancing VARIwise: towards autonomous irrigation and a grower's guide'.

9.2.3 Future research

More than 90% of irrigation of cotton in Australia is surface irrigation; hence, further work will be undertaken to evaluate the adaptive control framework in surface irrigation. This will be achieved in the proposed CRDC project 'Advancing VARIwise towards autonomous irrigation and a grower's guide'. This will provide a comparison of the control strategy performance with different spatial resolutions of data input and an analysis of the sensing requirement for site-specific adaptive control. The investigation of both irrigation and fertiliser application optimisation could also lead to further efficiency improvements.

9.3 RESEARCH COMMUNICATION

9.3.1 Journal papers

McCarthy, AC, Hancock, NH and Raine, SR (2013a) Advanced process control of irrigation: the current state and an analysis to aid future development. *Irrigation Science,* **31**(3):183-192.

McCarthy, AC, Hancock, NH and Raine, SR (2013b) Development and simulation of sensor-based irrigation control strategies for cotton using the VARIwise simulation framework. *Submitted to Computers and Electronics in Agriculture*

McCarthy, AC, Hancock, NH and Raine, SR (2013c) Simulation of irrigation control strategies for cotton using Model Predictive Control within the VARIwise simulation framework. *Submitted to Computers and Electronics in Agriculture*

McCarthy, AC, Hancock, NH and Raine, SR (2011) Real-time data requirements for model-based adaptive control of irrigation scheduling in cotton. *Australian Journal of Multi-Disciplinary Engineering*, **8**(2):189-206. ISSN 1448-8388.

9.3.2 Conference papers

McCarthy, AC and Hancock NH (2013) Development of a sensing system for automated fruit load and vegetation estimation. *In*: Australian Cotton Research Conference, 8-11 September, Narrabri.

McCarthy, AC, Gillies, MH and Smith, RJ (2013) Real-time, web-enabled adaptive control and monitoring of surface and overhead irrigation systems. *In*: Digital Research Futures Conference, 26-28 June, Armidale.

McCarthy, AC, Smith, RJ and Hancock NH (2012a) Real-time adaptive control of furrow irrigation: preliminary results of cotton field trial. *In*: 2012 Irrigation Australia Conference and Exhibition, 24-29 June, Adelaide.

McCarthy, A and Jensen, T (2012) Precision agriculture technologies for the Australian nut industries. *In*: ANIC 2012: Australian Nut Industry Research Forum, 21 September, Brisbane.

Raine, SR, Smith, RJ, McCarthy, AC, Gillies, MH and Hancock, NH (2011) Precision irrigation – it's more than just technology. *In*: LandWISE Annual Autumn Conference, 11-12 May, Havelock North, New Zealand. (keynote)

9.3.3 Poster

McCarthy, AC, Smith, RJ and Hancock, NH (2013) Implementation process of 'VARIwise' site-specific control strategies on surface and overhead irrigation. *In*: Australian Cotton Trade Show, 29-30 May, Moree.

McCarthy, AC, Smith, RJ and Hancock, NH (2012b) Real-time model predictive control of surface irrigation for cotton: setup of field trial. *In*: 16th Australian Cotton Conference, 14-16 August, Broadbeach.

McCarthy, AC, Hancock, NH and Raine, SR (2010) 'VARIwise' simulation of variable-rate irrigation of cotton via adaptive control: first results. *In*: 15th Australian Cotton Conference, 10-12 August, Broadbeach.

9.3.4 Planned journal papers

McCarthy, AC, Smith, RJ and Hancock NH (2014) Real-time adaptive control using Model Predictive Control and real-time flow rate adjustment. *Irrigation Science*.

McCarthy, AC, Smith, RJ and Hancock NH (2014) Real-time adaptive control of centre pivot irrigation: results of cotton field trial. *Agricultural Water Management*.

McCarthy, AC and Hancock NH (2014) Development and evaluation of plant monitoring system for estimation of fruit load and vegetation. *Journal of Cotton Science*.

9.4 INDUSTRY COMMUNICATION

I was awarded the NPSI/IAL Travel Fellowship Award 2010 and visited universities, USDA-ARS research stations and commercial variable-rate companies in the US for four weeks during March 2011. This fellowship has provided me with the opportunity to conduct a study tour into real-time sensing and control in irrigation that is relevant and valuable to my CRDC project.

I prepared a poster for the Precision Agriculture Symposium 2012 in September about the evaluation of uncertainty of irrigation application caused by wind drift from centre pivots (attached). This was presented by Professor Rod Smith.

I was a presenter at a field day for NCEA cotton research at my Jondaryan field site with the CRDC and Cotton Australia (February 2013) and the World Congress on Conservation in Agriculture in Gatton (September 2011). I was a presenter in the post-conference Smart-Farm tour for the Digital Research Futures Conference in June 2013 at Armidale. This demonstrated the real-time control and monitoring system in Jondaryan.

I visited Stahmann Farms at Moree in January 2012 to discuss possible irrigation optimisation opportunities. I regularly present my research results to visitors to the NCEA, from ACIAR, South Africa and Brazil, and at NCEA department seminars.

9.5 MEDIA ARTICLES

McCarthy, AC (2013) Adaptive control to improve surface irrigation efficiency. *The Australian Cottongrower Magazine*, December 2012-January 2013, pp. 24-26.

Noller, M (2012) In-row plant sensor cuts water use and increases crop yield. *The Australian Cottongrower Magazine*, June-July 2012. p. 51.

Smith, RJ and McCarthy, AC (2012) Precision irrigation in the Cotton Industry through adaptive control. *The Australian Cottongrower Magazine*, April-May 2012, pp. 27-28

McCarthy, AC (2011) NPSI/IAL travel fellowship 2010: site-specific irrigation control and sensing systems. *Irrigation Australia*, **26**(4). pp. 34-35. ISSN 0818-9447.

McCarthy, AC (2010) The land varies so should irrigation. *Spotlight Magazine*, Spring 2010.

Appendix A: Control strategy simulations with irrigation distribution variation

Table A.1: Performance of the iterative learning control strategy with irrigation uncertainty of ±10%, ±20% and ±50% standard deviation (replicates 1 to 10 for each uncertainty level); plus the corresponding result for correct irrigation application (simulation #1)

ID	Irrigation uncertainty	Rep	Yield (bales/ ha)	Total water applied (ML/ha)	Irrigation applied (ML/ha)	CWUI (bales/ ML_{total})	IWUI (bales/ $ML_{irrigated}$)
4	±10%	1	10.9 ± 2.2	11.6	7.8	0.9	1.4
5		2	10.7 ± 2.4	11.3	7.5	0.9	1.4
6		3	10.8 ± 2.5	11.5	7.6	0.9	1.4
7		4	11.2 ± 1.9	11.9	7.9	0.9	1.4
8		5	10.8 ± 2.2	10.8	7.2	1.0	1.5
9		6	10.8 ± 2.3	11.2	7.4	1.0	1.5
10		7	10.9 ± 2.5	11.7	7.9	0.9	1.4
11		8	11.2 ± 2.1	11.9	7.9	0.9	1.4
12		9	10.6 ± 1.9	11.4	7.6	0.9	1.4
13		10	10.8 ± 2.3	11.7	7.9	0.9	1.4
Nil		Average	10.9 ± 2.2	11.5 ± 0.3	7.7 ± 0.2	0.9 ± 0.1	1.4 ± 0.1
14	±20%	1	11.2 ± 2.5	11.9	7.9	0.9	1.4
15		2	10.5 ± 1.9	12.1	8.1	0.9	1.3
16		3	10.8 ± 2.6	11.2	7.4	1.0	1.5
17		4	10.4 ± 2.0	11.5	7.6	0.9	1.4
18		5	11.2 ± 1.9	11.9	7.9	0.9	1.4
19		6	10.4 ± 2.8	11.6	7.8	0.9	1.3
20		7	10.6 ± 2.2	11.7	7.9	0.9	1.4
21		8	11.1 ± 2.4	11.2	7.4	1.0	1.5
22		9	10.5 ± 2.9	11.6	7.8	0.9	1.4
23		10	10.6 ± 2.2	10.7	7.2	1.0	1.5
Nil		Average	10.7 ± 2.3	11.5 ± 0.4	7.7 ± 0.2	0.9 ± 0.1	1.4 ± 0.1
24	±50%	1	10.1 ± 2.6	10.9	7.3	0.9	1.4
25		2	10.5 ± 2.9	12.0	8.0	0.9	1.3
26		3	10.7 ± 3.2	11.9	7.9	0.9	1.4
27		4	10.3 ± 3.0	11.7	7.9	0.9	1.3
28		5	9.6 ± 2.5	11.3	7.5	0.8	1.3
29		6	9.7 ± 2.2	11.4	7.6	0.9	1.3
30		7	10.1 ± 2.5	11.6	7.8	0.9	1.3
31		8	10.4 ± 2.7	12.0	8.0	0.9	1.3
32		9	9.9 ± 2.6	11.2	7.4	0.9	1.3
33		10	9.8 ± 2.0	12.1	8.1	0.8	1.2
Nil		Average	10.1 ± 2.6	11.6 ± 0.3	7.7 ± 0.2	0.8 ± 0.1	1.3 ± 0.1
1	Nil	Nil	12.2 ± 1.5	11.0	7.3	1.1	1.7

Table A.2: Performance of the iterative hill climbing control strategy with irrigation uncertainty of ±10%, ±20% and ±50% standard deviation (replicates 1 to 10 for each uncertainty level); plus the corresponding result for correct irrigation application (simulation #2)

ID	Irrigation uncertainty	Rep	Yield (bales/ ha)	Total water applied (ML/ha)	Irrigation applied (ML/ha)	CWUI (bales/ ML_{total})	IWUI (bales/ $ML_{irrigated}$)
34	±10%	1	10.5 ± 1.8	12.7	9.0	0.8	1.2
35		2	10.8 ± 2.1	12.4	8.7	0.9	1.3
36		3	10.4 ± 1.9	13.1	9.2	0.8	1.1
37		4	10.9 ± 1.6	12.1	8.5	0.9	1.3
38		5	10.5 ± 1.7	12.2	8.6	0.9	1.2
39		6	10.1 ± 2.0	12.5	8.8	0.8	1.2
40		7	10.7 ± 1.8	12.9	9.1	0.8	1.2
41		8	10.8 ± 1.6	12.2	8.6	0.9	1.3
42		9	10.4 ± 2.0	12.4	8.7	0.8	1.2
43		10	10.5 ± 1.9	12.1	8.5	0.9	1.2
Nil		Average	10.5 ± 1.8	12.4 ± 0.3	8.8 ± 0.2	0.9 ± 0.1	1.2 ± 0.1
44	±20%	1	9.3 ± 2.2	12.4	8.7	0.8	1.1
45		2	9.6 ± 2.6	11.9	8.4	0.8	1.1
46		3	10.0 ± 2.7	12.7	9.0	0.8	1.1
47		4	9.2 ± 2.3	12.6	9.0	0.7	1.0
48		5	9.9 ± 2.5	12.1	8.5	0.8	1.2
49		6	9.7 ± 2.1	12.4	8.7	0.8	1.1
50		7	10.1 ± 3.1	12.2	8.6	0.8	1.2
51		8	9.7 ± 2.6	12.6	9.0	0.8	1.1
52		9	9.2 ± 3.0	13.1	9.2	0.7	1.0
53		10	9.8 ± 2.5	11.8	8.4	0.8	1.2
Nil		Average	9.6 ± 2.6	12.4 ± 0.3	8.7 ± 0.2	0.8 ± 0.1	1.1 ± 0.1
54	±50%	1	8.2 ± 4.2	11.9	7.9	0.7	1.0
55		2	9.2 ± 3.4	12.7	8.5	0.7	1.1
56		3	8.4 ± 3.7	13.0	8.6	0.7	1.0
57		4	8.0 ± 3.9	12.5	8.4	0.6	1.0
58		5	8.5 ± 3.8	11.6	7.7	0.7	1.1
59		6	8.6 ± 3.2	12.5	8.4	0.7	1.0
60		7	8.3 ± 3.3	12.1	8.0	0.7	1.0
61		8	8.5 ± 3.8	12.7	8.5	0.7	1.0
62		9	7.6 ± 3.9	13.0	8.6	0.6	0.9
63		10	8.6 ± 4.1	12.6	8.4	0.7	1.0
Nil		Average	8.4 ± 3.7	12.5 ± 0.4	8.3 ± 0.3	0.7 ± 0.1	1.0 ± 0.1
2	Nil	Nil	12.4 ± 1.6	12.2	8.1	1.0	1.5

Table A.3: Performance of the model predictive control strategy with irrigation uncertainty of ±10%, ±20% and ±50% standard deviation (replicates 1 to 10 for each uncertainty level); plus the corresponding result for correct irrigation application (simulation #3)

ID	Control strategy	Rep	Yield (bales/ ha)	Total water applied (ML/ha)	Irrigation applied (ML/ha)	CWUI (bales/ ML_{total})	IWUI (bales/ $ML_{irrigated}$)
64	±10%	1	12.5 ± 2.7	9.8	6.5	1.1	1.9
65		2	13.2 ± 2.8	8.8	5.9	1.5	2.2
66		3	12.4 ± 2.7	9.4	6.3	1.3	2.0
67		4	12.3 ± 2.6	9.6	6.4	1.3	1.9
68		5	13.1 ± 2.7	8.8	5.9	1.5	2.2
69		6	12.5 ± 2.1	9.6	6.4	1.3	2.0
70		7	12.7 ± 3.1	9.5	6.4	1.3	1.9
71		8	12.6 ± 2.8	8.9	6.0	1.4	2.1
72		9	12.7 ± 2.9	9.5	6.4	1.3	2.0
73		10	12.9 ± 2.5	10.1	6.8	1.3	1.9
Nil		Average	12.7 ± 2.8	9.5 ± 0.6	6.3 ± 0.3	1.3 ± 0.1	2.0 ± 0.1
74	±20%	1	12.5 ± 2.6	9.6	6.4	1.3	2.0
75		2	11.9 ± 2.9	10.1	6.7	1.2	1.8
76		3	12.1 ± 2.8	9.8	6.5	1.2	1.9
77		4	11.8 ± 3.1	9.7	6.5	1.2	1.8
78		5	12.2 ± 3.2	10.0	6.7	1.2	1.8
79		6	12.0 ± 3.0	8.9	5.9	1.3	2.0
80		7	12.5 ± 2.8	9.5	6.3	1.3	2.0
81		8	11.9 ± 2.6	9.2	6.1	1.3	2.0
82		9	11.8 ± 2.5	9.5	6.3	1.2	1.9
83		10	12.1 ± 3.2	9.7	6.5	1.2	1.9
Nil		Average	12.1 ± 2.9	9.6 ± 0.4	6.4 ± 0.3	1.2 ± 0.1	1.9 ± 0.1
84	±50%	1	11.2 ± 2.6	9.7	6.5	1.2	1.7
85		2	11.7 ± 3.2	9.5	6.3	1.2	1.9
86		3	11.5 ± 3.6	9.7	6.5	1.3	1.8
87		4	11.1 ± 3.3	9.1	6.1	1.2	1.8
88		5	11.6 ± 3.5	10.1	6.7	1.1	1.7
89		6	11.3 ± 3.1	9.8	6.5	1.2	1.7
90		7	10.9 ± 2.9	9.3	6.2	1.2	1.8
91		8	11.5 ± 3.2	9.5	6.3	1.2	1.8
92		9	11.2 ± 3.5	9.8	6.5	1.1	1.7
93		10	11.4 ± 3.4	10.0	6.7	1.1	1.7
Nil		Average	11.3 ± 3.2	9.7 ± 0.3	6.4 ± 0.2	1.2 ± 0.1	1.8 ± 0.1
3	Nil	Nil	14.3 ± 0.5	9.3	6.2	1.5	2.3

Table A.4: Performance of the iterative learning control strategy with light, moderate and strong wind in random wind directions; plus the corresponding result for correct irrigation application (simulation #1)

ID	Control strategy	Rep	Yield (bales/ ha)	Total water applied (ML/ha)	Irrigation applied (ML/ha)	CWUI (bales/ ML_{total})	IWUI (bales/ $ML_{irrigated}$)
64	Light	1	11.1 ± 2.1	10.8	7.2	1.0	1.5
65		2	12.5 ± 1.6	9.3	6.2	1.3	2.0
66		3	12.4 ± 1.9	9.2	6.1	1.3	2.0
67		4	12.8 ± 1.8	9.9	6.6	1.3	1.9
68		5	14.1 ±1.9	8.9	5.9	1.6	2.4
69		6	13.2 ± 2.0	9.7	6.4	1.4	2.1
70		7	11.2 ± 2.1	9.0	6.0	1.2	1.9
71		8	12.0 ± 1.9	9.9	6.6	1.2	1.8
72		9	11.9 ± 1.6	9.9	6.6	1.2	1.8
73		10	12.1 ± 1.8	8.8	5.8	1.4	2.1
Nil		Average	12.3 ± 0.9	9.5 ± 0.3	6.3 ± 0.4	1.3 ± 0.1	2.0 ± 0.2
74	Moderate	1	12.3 ± 1.8	10.7	7.1	1.1	1.7
75		2	11.4 ± 1.7	10.1	6.7	1.1	1.7
76		3	12.4 ± 1.9	11.5	7.6	1.1	1.6
77		4	11.4 ± 2.0	10.4	6.9	1.1	1.7
78		5	11.2 ± 2.1	10.8	7.2	1.0	1.6
79		6	12.7 ± 2.2	11.5	7.6	1.1	1.7
80		7	12.2 ± 2.1	9.7	6.4	1.3	1.9
81		8	10.2 ± 2.3	9.8	6.5	1.0	1.6
82		9	12.4 ± 2.0	11.9	7.9	1.0	1.6
83		10	10.3 ± 1.8	9.5	6.3	1.1	1.6
Nil		Average	11.7 ± 0.9	10.6 ± 0.8	7.0 ± 0.6	1.1 ± 0.1	1.7 ± 0.1
84	Strong	1	6.4 ± 2.1	13.8	9.2	0.5	0.7
85		2	7.4 ± 2.0	10.6	7.0	0.7	1.1
86		3	8.8 ± 2.2	13.8	9.2	0.6	1.0
87		4	7.6 ± 1.8	11.3	7.5	0.7	1.0
88		5	5.1 ± 1.9	10.0	6.6	0.5	0.8
89		6	7.7 ± 2.0	11.0	7.3	0.7	1.1
90		7	7.3 ± 2.1	13.1	8.7	0.6	0.8
91		8	7.8 ± 1.7	12.2	8.1	0.6	1.0
92		9	5.8 ± 1.5	13.6	9.0	0.4	0.6
93		10	7.9 ± 1.9	10.7	7.1	0.7	1.1
Nil		Average	7.2 ± 1.1	12.0 ± 1.4	7.9 ± 0.9	0.6 ± 0.1	0.9 ± 0.1
1	Nil	Nil	12.2 ± 1.5	11.0	7.3	1.1	1.7

Table A.5: Performance of the iterative hill climbing control strategy with light, moderate and strong wind in random wind directions; plus the corresponding result for correct irrigation application (simulation #2)

ID	Wind	Rep	Yield (bales/ ha)	Total water applied (ML/ha)	Irrigation applied (ML/ha)	CWUI (bales/ ML_{total})	IWUI (bales/ $ML_{irrigated}$)
4	Light	1	12.6 ± 2.1	12.8	8.5	1.0	1.5
5		2	12.2 ± 2.0	12.3	8.2	1.0	1.5
6		3	12.1 ± 2.0	11.3	7.5	1.1	1.6
7		4	11.7 ± 1.9	13.0	8.6	0.9	1.4
8		5	11.3 ± 2.2	13.3	8.8	0.8	1.3
9		6	12.6 ± 1.9	11.5	7.6	1.1	1.7
10		7	12.8 ± 2.3	12.4	8.2	1.0	1.6
11		8	12.0 ± 2.2	12.0	8.0	1.0	1.5
12		9	12.8 ± 1.8	11.8	7.8	1.1	1.6
13		10	12.7 ± 1.8	12.1	8.0	1.0	1.6
Nil		Average	12.3 ± 0.5	12.3 ± 0.6	8.1 ± 0.4	1.0 ± 0.1	1.5 ± 0.1
14	Moderate	1	11.5 ± 1.9	11.6	7.7	1.0	1.5
15		2	10.6 ± 1.8	12.2	8.1	0.9	1.3
16		3	11.7 ± 2.3	11.9	7.9	1.0	1.5
17		4	10.9 ± 2.2	12.1	8.0	0.9	1.4
18		5	11.1 ± 1.9	11.8	7.8	0.9	1.4
19		6	11.3 ± 2.3	10.6	7.0	1.1	1.6
20		7	11.5 ± 2.1	12.3	8.2	0.9	1.4
21		8	10.5 ± 2.1	11.9	7.9	0.9	1.3
22		9	11.9 ± 2.0	11.8	7.8	1.0	1.5
23		10	11.6 ± 1.8	12.4	8.2	0.9	1.4
Nil		Average	11.3 ± 0.5	11.9 ± 0.5	7.9 ± 0.3	1.0 ± 0.1	1.4 ± 0.1
24	Strong	1	6.8 ± 2.2	9.9	6.6	0.7	1.0
25		2	8.4 ± 2.3	11.2	7.4	0.8	1.1
26		3	10.1 ± 2.3	13.8	9.2	0.7	1.1
27		4	9.5 ± 1.9	12.0	8.0	0.8	1.2
28		5	8.0 ± 1.9	13.7	9.1	0.6	0.9
29		6	9.5 ± 2.0	12.1	8.0	0.8	1.2
30		7	7.3 ± 2.1	11.9	7.9	0.6	0.9
31		8	8.1 ± 2.2	10.9	7.2	0.7	1.1
32		9	8.5 ± 2.3	13.5	9.0	0.6	0.9
33		10	6.9 ± 2.2	10.0	6.6	0.7	1.0
Nil		Average	8.6 ± 1.0	12.3 ± 1.3	8.0 ± 0.8	0.7 ± 0.1	1.1 ± 0.1
2	Nil	Nil	12.4 ± 1.6	12.2	8.1	1.0	1.5

Table A.6: Performance of the model predictive control strategy with light, moderate and strong wind in random wind directions; plus the corresponding result for correct irrigation application (simulation #3)

ID	Wind	Rep	Yield (bales/ ha)	Total water applied (ML/ha)	Irrigation applied (ML/ha)	CWUI (bales/ ML_{total})	IWUI (bales/ $ML_{irrigated}$)
4	Light	1	12.4 ± 1.8	8.6	5.7	1.4	2.2
5		2	11.9 ± 1.9	9.9	6.6	1.2	1.8
6		3	12.2 ± 1.7	10.1	6.7	1.2	1.8
7		4	12.1 ± 2.1	10.7	7.1	1.1	1.7
8		5	12.3 ± 1.8	9.7	6.5	1.3	1.9
9		6	12.2 ± 1.7	8.6	5.7	1.4	2.1
10		7	11.8 ± 1.7	9.1	6.1	1.3	1.9
11		8	12.0 ± 1.6	9.0	6.0	1.3	2.0
12		9	12.2 ± 2.1	9.8	6.5	1.2	1.9
13		10	12.4 ± 1.8	8.7	5.8	1.4	2.1
Nil		Average	12.2 ± 0.2	9.4 ± 0.7	6.3 ± 0.5	1.3 ± 0.1	1.9 ± 0.2
14	Moderate	1	11.9 ± 1.8	10.2	6.8	1.2	1.8
15		2	11.3 ± 2.0	10.8	7.2	1.0	1.6
16		3	9.5 ± 2.1	10.4	6.9	0.9	1.4
17		4	10.6 ± 1.5	9.3	6.2	1.1	1.7
18		5	9.6 ± 1.5	9.8	6.5	1.0	1.5
19		6	10.1 ± 2.2	10.0	6.7	1.0	1.5
20		7	11.1 ± 2.3	10.5	7.0	1.1	1.6
21		8	11.8 ± 1.8	9.5	6.3	1.2	1.9
22		9	11.9 ± 1.7	9.4	6.3	1.3	1.9
23		10	11.1 ± 1.6	9.4	6.3	1.2	1.8
Nil		Average	10.9 ± 0.9	9.9 ± 0.5	6.6 ± 0.4	1.1 ± 0.1	1.7 ± 0.2
24	Strong	1	6.4 ± 2.2	9.7	6.5	0.7	1.0
25		2	7.3 ± 2.0	11.0	7.3	0.7	1.0
26		3	8.8 ± 2.1	10.8	7.2	0.8	1.2
27		4	8.6 ± 2.7	9.6	6.4	0.9	1.3
28		5	6.3 ± 2.5	9.1	6.1	0.7	1.0
29		6	10.0 ± 2.6	11.7	7.8	0.9	1.3
30		7	6.1 ± 2.3	11.1	7.4	0.5	0.8
31		8	8.3 ± 2.0	11.0	7.3	0.8	1.1
32		9	9.9 ± 2.5	9.2	6.1	1.1	1.6
33		10	9.0 ± 2.1	9.3	6.2	1.0	1.5
Nil		Average	8.3 ± 1.4	10.3 ± 1.0	6.9 ± 0.7	0.8 ± 0.2	1.2 ± 0.2
3	Nil	Nil	14.3 ± 0.5	9.3	6.2	1.5	2.3